INVESTIGATING PCA BASED TECHNIQUES FOR OBJECTIVELY MEASURING THE IMPACT OF THE FELDENKRAIS METHOD® ON PIANISTS' COORDINATION CHARACTERISTICS

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ABSTRACT

This thesis addresses the need for an objective means of measuring pianists' unique coordination characteristics that can examine movement relationships from many variables distributed throughout the body simultaneously during the performance of complex, bimanual piano playing tasks. Developing such a method would permit objective study of the effect of somatic methods, such as the Feldenkrais Method® (FM), on pianists' movement in future research. Lack of objective measurements in this field is related in part to the difficulty of measuring whole-body coordination during complex movements, like piano playing. Measuring coordination characteristics during complex movements is a critical challenge facing movement researchers. This thesis addresses this problem by exploring PCA-based (principal component analysis) approaches for identifying task-specific and pianist-specific coordination characteristics in the motion capture data of six advanced pianists performing a battery of twelve contrasting pianistic tasks at three motion capture sessions separated by one-week intervals. Each article of the thesis addresses a different aspect of this research problem. Articles one and two contextualize the problem by offering an analysis of the limitations of existing approaches for measuring posture and movement for assessing Feldenkrais outcomes relating to pianists' coordination. Article three assesses the limitations of standard PCA approaches for studying pianists' coordination characteristics. Article four proposes a novel framework for categorizing the different sources of task-determined and participant-determined variation layered in motion capture data to aid in the development of PCA procedures that target variation related to individual's coordination choices. Article five builds on the findings of the previous studies, presenting a new, PCA-based approach for identifying pianist-specific coordination characteristics that we call *Functional Subspace Identification*. Functional subspace identification compares inter-PC angles between pairs of PCs (principal components) from separate PCAs on subsets of the motion capture data to identify invariant, one-dimensional PC subspaces. The results show that functional subspace identification is an effective means of identifying task-specific variation characteristics that are common to all pianists, as well as variation characteristics unique to individual pianists. The findings of this thesis contribute to the study of coordination characteristics during complex movements in both musicians and non-musicians.

Keywords: principal component analysis, PCA, complex movement analysis, motion capture, piano performance, functional subspace identification, Feldenkrais Method

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PREFACE

The Research Ethics Boards of the University of Ottawa and Carleton University granted ethics approval for this research prior to the commencement of data collection. Ethics certificates can be found in Appendix A. I have received permission from Bloomsbury Publishing Plc to include copies of Articles 1 and 2 in this thesis, which are published in the volume *Feldenkrais in Creative Practice: Dance, Music and Theatre,* edited by Dr. Robert Sholl. Copyright permissions appear in Appendix B.

I, Jillian Beacon, carried out the research presented in this thesis, with the assistance and supervision of my co-supervisor, Dr. Donald Russell, and my supervisor, Dr. Gilles Comeau. Detailed contributions of each researcher to the articles are as follows:

Articles 1 & 2

I, Jillian Beacon carried out all literature review and analysis for these articles. Dr. Gilles Comeau found a suitable publisher for the articles and provided detailed feedback on the articles prior to their publication. Dr. Donald Russell reviewed the final articles to ensure they were ready for publication. Dr. Robert Sholl, editor of the book of publication, *The Feldenkrais Method in Creative Practice: Dance, Music, and Theatre* also provided feedback on the articles' structure organization prior to publication.

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I, Jillian Beacon planned the studies and data analysis, with the assistance and supervision of my co-supervisor, Dr. Donald Russell. Dr. Gilles Comeau assisted with participant recruitment. I recruited participants, collected the data, analyzed the data, and wrote the articles. Dr. Donald Russell authored the Matlab code used for data processing and provided detailed feedback on the articles throughout the various stages of writing. Dr. Gilles Comeau reviewed the final articles to ensure they were ready for submission and provided opportunities to present the work at the Music and Health Research Institute Conference. Members of my thesis committee assisted in the planning and execution of the project, including Dr. Heidi Sveistrup, who provided the lab space and equipment to carry out motion capture, and Dr. Erin Cressman, who provided valuable feedback on methodologies at the thesis proposal stage. I sought input from other researchers in the School of Human Kinetics prior to data collection, including Dr. Ryan Graham, who provided updated marker equipment and advice on optimizing the camera set up, and Dr. Matthew Mavor, who helped me learn how to use the Nexus software.

LIST OF FIGURES

CHAPTER 2

CHAPTER 4

(published, no thesis figure numbers)

CHAPTER 5

CHAPTER 6

CHAPTER 7

CHAPTER 8

LIST OF TABLES

CHAPTER 2

CHAPTER 4

(published, no thesis figure numbers)

CHAPTER 5

CHAPTER 6

CHAPTER 7

TABLE OF CONTENTS

CHAPTER 1: INTRODUCTION

1.1 Background

Expert pianists test the limits of the human motor system, coordinating their movement in some of the most complex and sophisticated ways humans are capable of. Surprisingly, despite their amazing movement abilities, pianists generally have a low level of awareness of their movement, and traditional piano pedagogy does not typically include explicit direction on body awareness, movement, or coordination. The lack of education on movement awareness comes at a price, with many pianists encountering frustrating limitations in the development of their musicianship and technique, or worse, developing playing-related pain syndromes. Somatic methods, such as the Feldenkrais Method®, can help fill this gap in pianists' education by offering strategies for developing improved body awareness and teaching movements that are more comfortable and efficient. However, despite the accumulation of subjective evidence that Feldenkrais training often leads to improvements in performance quality or pain symptoms for musicians, there is little objective research investigating whether participating in the Method leads to changes in pianists' movement characteristics. The lack of objective measurement is related in part to the difficulty of measuring whole-body coordination during complex movements like piano playing. Measuring coordination characteristics during complex movements is a critical challenge facing movement researchers. There are few existing analysis approaches that could help identify individual pianists' unique coordination characteristics by analysing moving relationships between many different parts of the body simultaneously during the performance of musical tasks. The purpose of this thesis is to address the need for new methods of analyzing motion capture data that allow researchers to identify whole-body coordination characteristics of pianists during the performance of bimanual musical patterns. Developing such a method would permit objective study of the impact of somatic methods, such as the Feldenkrais Method®, on pianists' movement in future research.

The following sections of this introductory chapter discuss the relationship between piano playing and complex motor coordination. The first section discusses the importance of studying complex movements in music performance as a means of better understanding of not only how the physical aspects of how piano playing are executed, but also how artistic meaning is contained in pianists' gestures. Reflecting on the centrality of complex movement to pianists' physical and artistic aspects of their performance explains why pianists may turn to methods such as Feldenkrais to address kinesthetic gaps in their education. The second part of the chapter provides background information on Moshé Feldenkrais and the development of his Method. The third part of the chapter explains the challenges of objectively measuring coordination characteristics to assess Feldenkrais outcomes and identifies Principal Component Analysis (PCA) as a mathematical tool that will be explored as the foundation for new approaches for measuring pianists' coordination developed in the research articles of this thesis.

1.1.1 Complex Coordination in Piano Playing

Although it is sometimes overlooked, proficient pianists' performance expertise relies not only on an advanced understanding of the aesthetics of musical interpretation, but perhaps more importantly on exceptionally developed motor coordination skills. Pianists must learn to coordinate the entire body to perform the complex harmonic and rhythmic patterns contained in advanced piano music. Controlling the timing, speed, loudness, and articulation of notes in the right- and left-hand parts simultaneously demands a high level of independent control over the movement of the arms. Pianists must also learn to coordinate the pelvis, spine, and head to support the arms and to aid in targeting the notes. Piano performance also requires independent coordination of the right and left feet to execute timed movements of the foot pedals. Developing such a highly refined ability to coordinate the different parts of the body requires many years of training, often starting in early childhood and extending for more than a decade into adulthood. Observing professional pianists execute these feats of coordination is often as breathtaking to watch as it is to listen to.

During their musical education, pianists tend to develop their exceptional coordination ability passively as they encounter new musical challenges. In the early years of classical piano training, improvements to motor dexterity and coordination develop largely from repeated practice of technical exercises and musical pieces that become progressively more complex as the student's skills develop. As the coordination demands of the music become more difficult, students gradually adapt and develop unique movement strategies for performance. However, mainstream piano pedagogy does not generally provide detailed guidance about how the body should be coordinated during piano playing. Most piano teachers pass on recommendations about playing posture and piano technique based on their own experiences or from established traditions. Even though pianists may first turn to their piano teachers for advice on optimal movement or reducing playing-related pain, few piano teachers possess sufficient training on issues related to motor control and musculoskeletal function to offer comprehensive advice on optimizing movement for better control of musical parameters and prevention of musculoskeletal injury (Baadjou et al., 2019; Bragge et al., 2008). In most cases, the quality of a pianist's performance is evaluated based on their communication of musical aesthetics, not on the quality of their movement. Therefore, many exceptional pianists have a sophisticated musical understanding of what they are doing when they are playing the piano but may not necessarily understand how they are doing it from the perspective of their own movement awareness.

Although some aspects of pianists' movement are primarily concerned with technical execution of the sound, other aspects of their movement communicate artistic meaning and reflect the performer's embodied understanding of the musical aesthetics (Leman & Godøy, 2010). In recent years the growing field of research on musical gesture has begun to explore the relationship between sound and movement, and to study the role of musicians' movements in helping the performer communicate meaning to realise a performance expressively (Delalande, 2003). A core aspect of this field of research has been the development of a taxonomy for classifying different types of musical gestures (Jensenius et al., 2010). For instance, movements that are required to produce musical sound on an instrument are referred to by some as *sound producing* gestures (Jensenius et al., 2010). *Sound facilitating* gestures are not directly involved in creating sound, but support sound production by facilitating a greater sense of the rhythmic pulse (entrainment), a sense of the phrasing, or a greater degree of control over sound producing movements (supportive movements) (Jensenius, 2010). Research in this field suggests *ancillary* (Wanderley, 2005), or *sound accompanying* (Jensenius, 2010) gestures appear to be an indispensable element of expressive music performance even though these types of gestures are not strictly required to produce musical sound on the instrument. For example, Wanderley (2005) conducted a study tracking the movement of the clarinet bell of five professional clarinetists during the performance of Stravinsky's *Three Pieces for Solo Clarinet* and found that the movements of the bell were closely related phrasing structures in the musical pieces for all performers, but that each clarinetist had their own unique approach to these movements. Furthermore, the movement patterns of the bell were stable for a given performer and musical piece over repeated performances (Wanderley, 2005). Interestingly, when clarinetists were asked to play "immobilized" (suppressing the sound accompanying/ancillary gestures and playing using only sound producing gestures) in a subsequent study, the motion capture discovered that the clarinetists continued to move in similar movement patterns as before, but with a smaller range of motion (Wanderley, 2005). This suggests that on some level a musicians' movement reflects their embodied musical understanding of the work such that the performance cannot exist as the performer understands it without the moving body as a mediator and executor. This idea is central in the field of embodied music cognition, which acknowledges the essential role of movement in the action and perception involved in listening to and making music (Leman, 2007; Schiavo et al., 2015). The concept of embodied cognition refers to the view that mental processes, such as thinking and reasoning, are not merely abstract processes taking place computationally in a neural executor but require participation of a moving actor. Action and cognition are not separate processes but are part of a continuity of experience by which an organism's sense of self and ability to learn, reason, and interact within the environment are facilitated by bodily experiences such as sensing and moving. This idea has strong ramifications for research on musicians' movement because it suggests, as Gabor observed that "musicians can only become musicians when they make use of the knowledge within their bodies." (Gabor, 2013, p. 210). It therefore follows that we cannot truly study musical gestures unless we study the musician in the act of making music.

As pianists accumulate years of practice and encounter music that is more technically demanding it becomes increasingly likely that they may confront musical or physiological challenges they cannot overcome without developing a greater awareness of the movement aspects of their craft. When the body becomes an obstacle rather than an instrument of musical communication, as may occur with the development of playing related pain or injury, the musician suffers not only a physical health problem but also confronts a crisis of the self-knowing (Gabor, 2013). For expert musicians, being unable to use one's body to make music can be deeply disorienting. Most musicians will have started their training at such an early age that their musical development is inseparable from their personal maturation, and losing the ability to perform can feel like losing one's identity. Therefore, the pursuit of excellence in musical performance and desire for a more embodied understanding of how the one's movement relates to one's musical identity drives many to seek out somatic training methods as a means of refining the motor aspects of their performance, which are often overlooked during the formative years of training. Somatic training methods are educational approaches that offer strategies for developing a greater awareness of subtle sensations related to body movement, positioning, balance, and orientation to improve the ease and fluency of movement (Eddy, 2009; Hanna, 1988). At the foundation of most somatic methods is an appreciation of the interconnectedness of the mind and body as a continuity rather than separate entities (Feldenkrais, 1964/2010). They seek to help students learn to recognize their own habitual movement characteristics which may be causing them pain or limiting their agility. As students gain more experience with somatic methods, they learn new ways of coordinating movement that are theorized to be more effective and place less strain on musculoskeletal structures. Unfortunately, for many performers, the exploration of movement awareness through somatic training begins only after signs of playing-related pain or injury have started to develop. For many, years of practicing without considering how the body is used in performance can result in frustration due to limitations in technical execution, or worse, painful musculoskeletal pain syndromes which, in serious cases, may prevent the pianist from playing entirely (Corrêa et al., 2018).

1.1.2 The Feldenkrais Method® of Somatic Education

The Feldenkrais Method® is a somatic approach that many musicians have sought out to improve movement awareness during performance or to help address playing-related pain (Burrell, 2021; Fraser, 2021). The Method was developed by Dr. Moshe Feldenkrais (1904-1984), an engineer and Sorbonne-trained physicist who also became a Judo master, establishing the Ju-Jitsu Club de France during his time as a doctoral student in Paris (Reese, 2015). He spent time teaching Judo to help finance his studies, even teaching the Nobel laureates Frédéric and Irène Joliot-Curie, with whom he worked as a research assistant in the Radium Institute (now known as the Curie Institute) (Feldenkrais, 1979/2010). Feldenkrais fled Paris at the outset of WWII and worked as a sonar researcher on submarines during the war. During his work for the British military, he aggravated an old knee injury sustained from playing soccer in his earlier years. Doctors recommended surgical correction, but Feldenkrais refused, opting to attempt to improve the function of his leg on his own by carefully observing his movements and exploring how different ways of moving impacted his perception of pain and ability to walk comfortably.

These early studies in detailed self-observation marked the beginning of the development of his Method. After the war, he spent time in London where he continued to teach Judo and further developed his ideas on enhancing motor function through movement awareness. Eventually he moved to Israel where he became a state engineer. By 1954, Feldenkrais had transitioned his career to give his full attention to teaching and developing his Method. He began instructing others to teach his techniques, training the earliest Feldenkrais Practitioners in Tel Aviv from 1969 to 1971 (Strauch, 1996). Feldenkrais traveled with these new practitioners, teaching the Method throughout Europe and North America until his death. Today there are Feldenkrais Institutes and Guilds around the world that offer four-year accredited professional training programs to train Guild Certified Feldenkrais Practitioners (GCFPs).

Over the course of his life, Feldenkrais' exploratory work on improving motor function through enhanced sensorimotor awareness gradually led to the crystallization of the ideas and techniques central to his Method. Feldenkrais saw movement as a universal constant at the heart of learning and a conduit to self-knowledge for each person (Feldenkrais, 1990). He recognized that structured exploration of movement could be used to improve function and enhance self-awareness for anyone, since learning through movement developmentally precedes all other forms of human learning (Feldenkrais, 1981). He believed that authentic motor learning required engaging in a process of playful sensorimotor exploration, similar to how infants develop their sense of self and improve their motor coordination while exploring their environment through touch and movement (Feldenkrais, 1990). Feldenkrais found that most adults he worked with had lost touch with the ability to learn through attending to sensation. Therefore, teaching students to 'learn to learn' by becoming more aware of subtle sensations related to position, orientation, sense of balance, and sense of muscle tonus became central to the Method (Feldenkrais, 1961/2010). During his years of teaching Judo and working with individuals with injuries or motor disabilities he observed that people's manner of moving often became habituated and difficult to change, persisting even when the movements were ineffective or elicited pain (Feldenkrais, 1962). Therefore, Feldenkrais sought to help his students develop motor adaptivity rather than teaching specific postural characteristics. He developed techniques designed to wake up individuals' sensory acuity so they could respond adaptively to their environment rather than with stereotyped motor responses (Feldenkrais, 1985). He believed that the health of an individual is strongly related to their ability to adapt to new circumstances (Feldenkrais, 1979/2010). He developed his Method to be non-corrective, encouraging individuals to use their own sensations to guide them in choosing optimal movement strategies rather than attempting to replace existing movement habits with alternatives deemed by others to be more 'correct'. Students of the Feldenkrais Method® learn to evaluate the quality of their movement based on their sense of ease, smoothness, and functionality.

1.1.2.1 Awareness through Movement. Feldenkrais developed two primary modes of sensorimotor learning that continue to be employed in the Method today: *Awareness through Movement* (ATM) and *Functional Integration* (FI). During an ATM lesson, students follow verbal instructions from a Feldenkrais practitioner who guides them through a structured series of movements exploring specific functional relationships between different parts of the body (Feldenkrais, 1990). Feldenkrais developed hundreds of ATM lessons throughout his life, and while some advanced practitioners develop their own lessons, most teach ATM based on the fundamental elements in Feldenkrais' own lessons. ATM is often done lying down but can also be done seated or standing. Most ATM lessons begin with a body scan, during which the students attend to their current state of body organization, including their sense of contact with the floor, the orientation of different parts of the body, and their sense of muscle tonus. After the scan, the practitioner begins instructing the students through a series of movements. The students are encouraged to move slowly and with attention, resting between each repetition to ensure each movement is done mindfully. The practitioner directs students to attend to the sensations they experience throughout their bodies as they move, such as the perception of movement transfer between different parts of the body, the perception of muscle softness or tension, their sense of balance, the sense of contact with the floor, the orientation of various parts of the body in relation to the room, and the speed and direction of movements. Throughout the lesson, the practitioner encourages students to move only in ways that feel easy, exploring how they can simplify the movement and reduce any unnecessary effort. Practitioners orient students to conceive of how the movements are experienced throughout the entire body. The slow and mindful quality of the movements encourages sympathetic nervous system dominance and students generally begin to feel more relaxed and focused as the ATM lesson progresses. ATM lessons are punctuated by frequent rests that allow the activity in the nervous system to quiet and give the nervous system time to integrate the sensory experiences. The movements gradually become more complex as the student explores novel variations that experiment with new movement combinations, directions, and timing patterns. Movement novelty is an important strategy employed during ATM because it encourages the student to move in non-habitual ways, promoting neuroplastic adaptivity in the sensory motor system. For instance, practitioners may instruct students to turn the head to the right while directing the eyes to the left. This unfamiliar way of coordinating the head and eyes requires the students to attend more carefully to their movements to sense how it can be done. These novel coordination instructions can be difficult for students to achieve. Practitioners encourage students not to strive to achieve them, but to approach them playfully, as a child would a game. At the very heart of the Method is the idea of encouraging people to seek out the fundamental joy of moving with ease and lightness.

1.1.2.2 Functional Integration. The second mode of learning, *Functional Integration* (FI)*,* could be described as a non-verbal dialogue between two nervous systems communicating through touch and movement. At the beginning of an FI lesson, the practitioner observes their student moving in various seated, standing, or lying positions to sense, feel, and see patterns of movement, coordination, and muscular tension characterizing the student's movement (Feldenkrais, 1981). The student then relaxes, usually lying down on a low table, and the practitioner begins to gently move parts of their body through various movement sequences. The practitioner does not seek to push, pull, or force the body into any pre-specified orientation, and avoids movements where resistance is detected. Instead, the practitioner seeks to join with the student's existing movement tendencies by carefully attending to the sense of ease, lightness, or resistance in the student's body. For instance, the practitioner may gently lift the legs one at a time to sense which feels easier or lighter to lift. They may gently push through the length of each leg one at a time by applying pressure to the sole of the foot to see how the movement transfers from the leg to the pelvis, up the spine, and to the head. The practitioner moves only in ways that feel comfortable and familiar to the student. The principle of "joining" distinguishes Feldenkrais from many other modalities; by joining the student in following what already feels natural to them, the nervous system experiences a sense of safety that allows the student to further relax. The student senses the ease and lightness that comes from being supported rather than the resistance that comes from pushing or prodding them into unfamiliar positions. Physiologically, the practitioner takes over the work of the muscles by moving the person's body for them. This encourages the nervous system to let go of unnecessary or latent tonicity in the muscles. As the student becomes increasingly relaxed, the practitioner introduces new movement sequences that invite the student to experience possibilities for coordination they may not have been aware of before. Allowing the practitioner to take on the role of directing movement gives the student a unique sensory perspective, helping them to actively observe the sensations of the movements being highlighted by the practitioner without having to direct the movements themself. Although the student consciously attends to movement sensations during an FI, Feldenkrais theorized that the nervous system registers the sensory experiences of the new movements on a subconscious level so that the student does not have to work to memorize and later cognitively reproduce the sensorimotor information learned during an FI. Rather, Feldenkrais theorized that the nervous system integrates the sensorimotor experiences of the lesson such that with repeated FIs, the nervous system will begin to spontaneously integrate the sensorimotor experiences into adaptative movement in the student's daily life.

1.1.3 The Challenge of Objectively Measuring Feldenkrais Outcomes with Musicians

Anecdotally, some musicians report feeling that the quality of their performance improves after experiencing lessons in the Feldenkrais Method® (Burrell, 2021; Chiang, 2023).

Some also experience improvements in playing-related pain symptoms (Nelson, 1989; Rywerant, 2003). Theoretically, these reported improvements could be linked to changes in musicians' coordination characteristics, since the Feldenkrais Method® is directed at helping individuals learn how to adapt their movement strategies to decrease musculoskeletal strain and enhance the ease of motion. However, there are very few objective studies investigating if the Feldenkrais Method® is successful in altering coordination characteristics in musicians. Most of the existing research relies on subjective evidence, such as practitioner or student-reported outcomes. Studies are needed that objectively measure whether participating in Feldenkrais lessons changes musicians' movement characteristics, and if so, what kind of changes are observed.

The concept of measuring how movement training interventions impact movement characteristics is not new in human kinetics research. Optical-based motion capture tools offer the technology required to accurately track the position of reflective markers placed on the human body allowing researchers to compare movements from before and after interventions. However, finding data analysis techniques to measure the impact of interventions like the Feldenkrais Method® on whole-body coordination characteristics during complex movements, such as those required in piano playing, poses unique challenges to researchers searching for evidence of changing coordination characteristics in the immense data sets generated by motion tracking. Existing methods that have been used to measure outcomes of other forms of somatic training often involve measuring static postures or finding the average positions of joints across many measurements (Beacon et al., 2021a; Ohlendorf et al., 2017; Rousseau et al., 2023; Wong et al., 2023). Methods measuring static postures or finding average body positions during complex movement are not suitable for assessing Feldenkrais outcomes because the Method seeks to affect dynamic modulation of whole-body coordination strategies.

Many methods for studying movement dynamically rely on limiting the complexity of the moving system by restricting the study to a small number of discrete kinematic variables within the musculoskeletal system. This requires *a priori* selection of discrete kinematic variables expected to be influenced by the movement retraining intervention. In the case of the Feldenkrais Method®, it is difficult to choose specific variables to measure *a priori*, since everyone will present with unique movement characteristics and histories of injury or playing-related pain. It is expected that movement outcomes will vary from person to person as each individual responds to Feldenkrais training according to their own needs. Furthermore, studying the movement of individual joints does not give a sense of how different parts of the body are coordinated. It is likely that after experiencing Feldenkrais lessons, the change in movement characteristics observable for any one joint may be very small, and difficult to distinguish from natural motor variability in the motor system. However, when considered together, small changes distributed across many joints may provide meaningful information about the reorganization of an individual's coordination characteristics. Therefore, conducting a thorough and meaningful assessment of the impact of Feldenkrais lessons on coordination across the body requires methods of measurement that can help assess how movements of different parts of the body are related to each other.

Measuring whole-body coordination characteristics in the context of musical performance adds another layer of complexity to the problem. Patterns related to the rhythmic, harmonic, and melodic content of the music being performed add pre-determined variation into the motion capture data set that are layered with variation related to the participant's unique coordination characteristics. Studying subtle changes to whole-body coordination during piano playing requires measurement methods that allow the researcher to find evidence of movement relationships outside of those expected based on the musical patterns.

One analysis method which permits the study of relationships between many different variables simultaneously is Principal Component Analysis (PCA). PCA is a method derived from linear algebra which can decompose the variance in complex data sets into independent principal components (PCs). The PCs are a ranked list of vectors, each describing a different proportion of the total variation in the data set (Daffertshofer et al., 2004). PCA is a linear transformation of the data, and the PC vectors can be multiplied by corresponding weighting vectors to reconstruct the original data. PCA does not change the data but provides a way of representing the data which illustrates independent variation structures (principal components) existing between variables in the data.

Researchers have used PCA in previous studies to gain insight into the fundamental variation characteristics of different types of human movement, such as gait (Troje, 2002), or to compare movement characteristics between different experimental groups, such as people with and without a motor control disorder (Dillmann et al., 2014; Kobayashi et al., 2014). However, the ability of PCA to help identify subtle differences in coordination characteristics over repeated trials has not been tested, and it has only been used in a few studies on musical movement. It is possible that the characteristics of the principal components identified by PCA in a data set representing body movements from various anatomical markers distributed throughout a pianist's body may be sensitive to subtle changes in body coordination brought about by the reorganization of various aspects of movement during somatic training. It is hypothesized that somatic training may bring about considerable overall organizational change to movement coordination such that if you measure any one postural variable individually, the change to that variable before and after somatic training will be very small and indistinguishable from day-to-day expected fluctuation in posture/motor behaviour. However, the overall effect of many subtle changes in how different parts of the body are coordinated is potentially more important than any individual change in average position that may occur at a selected joint or body part. By measuring a small number of postural variables and attempting to quantify their individual meaning within the larger moving system we run the risk of missing important features that may suggest that pianists' overall coordination characteristics may be shifting in response to somatic training. Studying the characteristics of the PCs identified by PCA may provide researchers with a means of monitoring underlying coordinative changes in pianists' movements as they alter their habitual movement patterns in response to somatic training that may not be detectable by measuring individual postural variables.

1.2 Purpose of Thesis

The purpose of this thesis is to address the need for an objective means of measuring pianists' coordination characteristics that can be used to identify movement relationships throughout the body during musical performance. Developing such measurement tools will be required to carry out future research investigating how somatic methods, like the Feldenkrais Method®, influence individual pianists' coordination characteristics.

This line of research is motivated, in part, by previous research studies conducted by the University of Ottawa Piano Pedagogy Research Laboratory on exploring somatic methods as a means of supporting musicians' health and wellness. For example, in a previous project, Slade and colleagues (2018) studied the effects of Body Mapping training on audible aspects of pianists' performance by collecting MIDI (musical instrument digital interface data) such as key-press timing and note loudness during the performance of technical exercises before and after a one-day Body Mapping workshop. The researchers also collected video data of the performers playing the technical exercises before and after the workshop which were submitted to visual analysis by body mapping practitioners. The study found that pianists did not demonstrate measurable change in note timing and loudness after a single Body Mapping Workshop. Any changes noted were below the threshold of being audibly observable by listeners. By contrast, body mapping practitioners were able to identify the post-test videos of pianists' performances without the sound playing 64% (p <.001) of the time, suggesting that in some cases Body Mapping leads to visually observable changes in body movement and positioning. In a second study, Wong and colleagues (2022) conducted a motion capture study examining whether 10 Alexander Technique lessons distributed over a two-week period influenced the average magnitude of postural angles related to head, spine, shoulder, and pelvic orientation of 15 pianists. The results indicated a statistically significant change to the size of craniovertebral and head-neck-trunk angles as well as various angles related to the thoracic and lumbar curves of the spine. The changes suggested increase in spinal extension post Alexander lessons. In contrast, my thesis seeks to develop an alternative method for assessing changes to musicians' movement that could help identify pianists' unique coordination characteristics by studying variation in movement data collected from anatomical markers distributed throughout the body. Rather than taking the approach of selecting specific postural variables *a priori*, this thesis seeks to develop a method of studying the variation characteristics in pianists' movement to identify participant-specific and task-specific features in the movement variation that could be tracked over time to find out if somatic methods, such as the Feldenkrais Method, influence how pianists' coordinate their movement during performance. By isolating participant-specific variation characteristics we hope to create a new type of dependent variable that can be used to detect evidence of change to movement coordination in pianists that may result from participating in somatic training that is movement-focused rather than posture-focused.

The articles in this thesis address this topic in two ways:

1. Articles one and two contextualize the problem by offering an analysis of the limitations of existing approaches for measuring posture and movement for assessing Feldenkrais outcomes relating to pianists' coordination.
2. Articles three, four, and five explore novel PCA-based approaches for gaining insight into pianists' coordination characteristics. Article three explores the limitations of current PCA approaches for identifying task-specific and pianist-specific coordination characteristics. Articles four and five and propose new PCA procedures that make it possible to identify pianist-specific coordination characteristics.

This is a conceptual thesis that examines the motion capture data of six advanced pianists to study the relationships between PCA results and pianists' coordination characteristics during different types of pianistic tasks. The six pianists performed twelve different musical tasks repeated three times at the interval of one week. The findings of each article build sequentially to gradually shape new procedures for applying PCA that are more suitable for identifying pianists' unique coordination characteristics. The thesis focuses on exploring existing approaches for PCA measurement and improving them so that they can be applied in future research to gain a better understanding of the impact of Feldenkrais training on pianists' coordination characteristics. The specific contributions of each article to the topic are described in the following sections.

1.2.1 Article 1 Purpose- The Feldenkrais Method® for Musicians: Addressing the Need for Objective Measurements

The first article reviews the existing literature on subjective and objective means of evaluating movement outcomes of somatic training with musicians. The paper highlights the need for more objective measurements and identifies why many common quantitative approaches to posture measurement are of limited value for studying how Feldenkrais training may influence cross-body coordination characteristics of pianists. This article is published in chapter six of the book *Feldenkrais in Creative Practice: Dance, Music, and Theatre* edited by Robert Sholl (Sholl, 2021; Beacon, Comeau, & Russell, 2021a).

1.2.2 Article 2 Purpose-Gaining Insight on the Impact of Feldenkrais Functional Integration in the Context of piano Playing: Considerations for Measuring Posture and Movement Quality

Article two contains two parts. Part one builds from the results of a previously conducted pilot study using two-dimensional video-based motion capture software to compare individual pianists' movement characteristics on a small number of tasks before and after a single Feldenkrais FI lesson (Beacon, 2015). The article presents examples from the pilot study that are interpreted to show why studying whole-body movement patterns offers more powerful insight into pianists' coordination than average postural measurements. Part two proposes recommendations for future research design and identifies PCA as a previously unexplored measurement approach in somatic research that could offer a means of identifying coordinative relationships between the movement of various parts of the body. This article is published in chapter seven of the book *Feldenkrais in Creative Practice: Dance, Music, and Theatre* edited by Robert Sholl (Sholl, 2021; Beacon, Comeau, & Russell, 2021b).

1.2.3 Article 3 Purpose-Evaluating Standard PCA as a Tool for Measuring Coordination Characteristics in Pianists

The third article of this thesis tests the suitability of standard PCA approaches for identifying participant-specific and task-specific coordination characteristics of pianists during the performance of four pianistic tasks of different complexity over a three-week trial.

We posed the following research question:

Are standard PCA output values capable of distinguishing subtle differences in movement patterns brought about by:

1. Differences in musical task complexity;
2. Differences arising from learning effects resulting from practicing the task at each trail; and
3. Inter-individual differences between pianists?

We hypothesized that:

1. Standard PCA output values may vary between tasks of varying levels of complexity due to the possibility pianists may freeze degrees of freedom when confronted with an unfamiliar task;
2. Standard PCA output values may not vary over the three trials for simpler tasks since pianists would likely be able to perform simpler tasks in a consistent manner without

additional practice. However, PCA output values may vary from trial one to trial three for more complex tasks as pianists gain more experience; and

3. Standard PCA output values would vary between pianists for the various tasks, since pianists were able to choose their own tempos, musical inflection, and would apply their own unique techniques.

The results show that standard PCA output values are not sensitive enough to detect differences in any of these three cases.

1.2.4 Article 4 Purpose-A Novel Framework of Variation in Music Performance for Planning Targeted PCA as a Tool for Measuring Coordination Characteristics in Pianists

The fourth article of this thesis extends the analysis of the findings of the previous article to consider why PCA was unable to detect differences in pianists' coordination characteristics arising from task-complexity, learning effects, or inter-individual differences. The methodology used a process of visual inspection of raw-motion capture trajectories and waveform plots of individual principal components from PCA analyses to look for evidence of different sources of variation layered in the motion capture data. We compiled the results of these observations and summarized them in a *theoretical framework of variation in music performance* that identifies different musical and biomechanical sources of variation contributing to the overall variation in the data set. This framework identifies fixed sources of variation related to task requirements and anatomical constraints that do not change between participants. It also identifies sources of variation that are free to vary based on the musical and biomechanical choices of the performer. The article discusses the value of the theoretical framework in terms of its ability to help researchers consider the landscape of different variation sources contributing to their data sets to help develop PCA approaches that target experimentally relevant variation that may be hidden inside the data set.

1.2.5 Article 5 Purpose-Functional Subspace Identification: A Technique for Assessing Coordination Characteristics in Complex Tasks by Locating Invariant Principal Components in Subsets of Movement Data

The fifth article applies the conceptual framework developed in article four to explain how a novel PCA approach we developed and refer to as *functional subspace identification* can be used to gain insight into both task-determined and participant-determined coordination characteristics of various pianistic tasks. We identified that looking for invariant principal components that are common to different subsets of the motion capture data can provide insight into pianists' coordination characteristics. This process provides a means of linking certain variation characteristics to specific groups of anatomical markers and can identify independent coordinative structures that exist within the larger data set. Article five concludes with recommendations for future work to further refine the process of functional subspace identification by proposing a possible means of removing fixed variation related to the musical pattern prior to PCA to further target participant-specific coordination characteristics.

1.3 Statement of Primary Research Question

The general research question uniting the individual papers of this thesis is:

Can we find a way of objectively identifying coordination characteristics related to an individual pianist's unique way of moving their body during the performance of a given musical task that relates to how movements are coordinated throughout the body rather than isolating individual postural variables for measurement?

The specific research question that will be investigated by the research articles three, four, and five of this thesis is:

Can we develop a PCA-based strategy for analysing the motion capture data of pianists that allows us to better understand overlapping sources of variation in the data and permits the identification of both task-determined and participant-determined movement coordination characteristics unique to individual pianists?

Successfully answering these research questions will result in the development of a new means of objectively measuring coordination characteristics unique to individual pianists that arises from studying variation characteristics in the motion capture data. The PCA-based tools for identifying such coordination characteristics could be applied in future research as a means of measuring a new type of dependent variable for assessing changes to pianists' coordination characteristics that may result from somatic training methods, such as Feldenkrais. This method of assessment would be better aligned with both the complexity of movement inherent in musical performance and the goals of Feldenkrais which seek to influence movement coordination throughout the body rather than the function of individual joints or joint systems.

1.4 Original Research Contributions

This thesis makes the following original research contributions to the fields of musicians' health and human kinetics:

1. This thesis contributes to the field of musicians' health research by providing an evidence-based rationale supporting the objective study of dynamic coordination characteristics rather than the measurement of average body positions or static postures in research on somatic training outcomes for musicians. The idea that posture is static

persists in music pedagogy, and many music researchers may not know of alternatives to measuring static postural alignment or average body positions as a means of assessing how musicians may respond to somatic training. This thesis contributes a new PCA-based approach to measuring coordination characteristics in pianists that will help make movement-based study of pianists' coordination more accessible to those transitioning into the world of research from a background in the musical arts.

2. This thesis contributes to the field of complex movement analysis in human kinetics by exploring the strengths and limitations of PCA as a tool for gaining insight into coordination features during piano playing. The results of this thesis make several original contributions to this field, including:
    a. The development of a novel *Theoretical Framework of Variability in Music Performance* to guide future researchers toward a more detailed consideration of the different sources of variation within complex motion capture data. Although PCA is a means of analysing variation in the data, previous research applying PCA in the context of human movement rarely considers how different sources of variation contribute to the overall variation in a data set. The framework provides researchers with a tool for conceptualizing the different sources of variation present in motion capture data to help plan PCA procedures that target variation related to pianist-specific coordination characteristics. Although we developed the framework for research with musicians, the concept could be adapted to assist in conceptualizing variation sources for PCA studies of other types of complex movement.

b. The development of *Functional Subspace Identification* as a new approach for using PCA to study task-specific and participant-specific coordination characteristics in complex movements. The procedure we have developed has not been previously described in research. It could provide researchers with a means of identifying participant-specific coordination characteristics that could be measured over time to track the impact of movement retraining interventions.

The articles of this thesis successfully address the need for new measurement approaches which facilitate the study of coordinative relationships between many different parts of the body during complex movements generated from music performance. The new conceptual framework and novel PCA approach for measuring pianists' coordination characteristics that will be useful in future studies measuring the impact of Feldenkrais training on pianists' movement.

CHAPTER 2: STUDYING VARIATION IN COMPLEX MOVEMENTS

2.1 Introduction

The purpose of this thesis is to address the need for an objective means of measuring pianists' coordination characteristics that is sensitive to subtle changes to movement relationships distributed throughout the body during pianists' complex movements. We are motivated to develop such measurement approaches to apply them in future research evaluating the impact of somatic methods, such as the Feldenkrais Method®, on pianists' coordination characteristics. Existing research on somatic methods with musicians is reviewed in article 1 (chapter 3) of this thesis, which contextualizes why objective research in this field is urgently needed. Literature pertaining to the reasons musicians may seek out somatic training, such as playing-related pain, also appear in article 1 (chapter 3) and article 2 (chapter 4). Rather than reiterating that literature, this chapter provides background about the challenges researchers face when analyzing movement relationships existing within multi-variable motion capture data sets during complex human movement, since this is the challenge at the heart of the research questions of this thesis. This chapter begins by briefly reviewing different measurement approaches researchers have used when attempting to quantify meaningful information about variation in complex human movements. Variation in this case refers to the mathematical concept of quantifying the relationship of one or many variables to one or many other variables. The opening section discusses strengths and limitations of various approaches in terms of their ability to identify pianist-specific coordination characteristics that could be measured and tracked over time in future intervention studies. The second section discusses Principal Component Analysis (PCA), which is the analysis approach we chose to investigate in this thesis. We explain what it is, give an overview of how it has been used in previous research on human movement, and provide a simplified example of how it can be applied to motion capture data of a single marker on a pianist's wrist to help the reader understand how PCA is applied in articles 3, 4, and 5 of this thesis and what kind of information it provides. The explanations are intended to be conceptual rather than purely mathematical so that readers without a background in mathematics can engage with the core concepts of PCA.

2.2 Methods of Measuring Variation in Complex Movements

The term "complex movement" is frequently used but seldomly defined in human kinetics research. Complex movements generally require the coordination of many degrees of freedom distributed throughout the entire body (Wulf et al., 1998). In sports and exercise rehabilitation, complex movements are usually those which require movement in more than one plane or around more than one axis of rotation, targeting many muscle groups simultaneously (Giannakopoulos et al., 2004). The complexity of movements is often determined comparatively within a study. For instance, researchers may devise a battery of tasks to study that range from simple to more difficult to execute, such as comparing simple key tapping to playing sequences of piano keys with four fingers (Verstynen et al., 2005). Others define complex movements as those that require a greater amount of practice or rehearsal to master (Wulf & Shea, 2002). Most of the time, complex movements refer to real-world movements that can be influenced by various intrinsic and extrinsic factors, rather than to simplified and highly constrained experimental movements. Levac and colleagues (2019) give a comprehensive description of complex movement based on this concept, defining complex motor skills as those involving nested redundancies in both the musculoskeletal and neuromotor possibilities for executing the parameters of a task, as well as in the number of possible solutions that can be considered as successful task outcomes.

No matter which definition is used, bimanual performance of musical patterns at the piano certainly meets the criteria to be considered a highly complex form of human movement. The level of independence required in the movement of the right and left arms, feet, and torso coordinating in response to integrated visual, auditory, and tactile sensory information simultaneously may make piano playing one of the most complex motor activities human beings can perform (Goebl, 2017). Analysing coordinative features of whole-body movements of pianists poses a challenge several order of magnitudes more complex than is typically confronted in human movement research. When confronted with the prospect of gaining an understanding of how movement variables are related during complex movements, researchers can either control the variation by simplifying the system being studied through isolating specific variable interactions and then inferring relationships between these interactions *post hoc*, or they can preserve the complexity of the system and apply mathematical strategies for deriving quantitative markers pointing to variability characteristics that may contain information about how variables interact within the system. The goal of this thesis is to develop a method that can reveal meaningful relationships between multiple movement variables simultaneously while preserving a high degree of complexity in the data by studying motion capture data from across the bodies of pianists performing realistic, bimanual pianistic tasks. The following sections describe some of the analytical options that have been explored in previous research and discusses their strengths and limitations for studying pianists' coordination characteristics.

2.2.1 Phase Relationships

Historically, one of the most common ways to study coordination is to examine the relative phase of the movement of two joints by computing the phase angle between them (Wheat & Glazier, 2005). This can be done by computing the angle of each joint at a specific moment in time and calculating the difference between the two, either discretely (choosing specific moments in time) or continuously (comparing changes to the phase relationship over time) (Dubois et al., 2023). Phase relationships can be computed based on position or the first derivative of position, velocity. Measuring phase relationship in joint couplings is an established approach in the study of coordination in human gait (Van Emmerik et al., 2005a). For instance, Van Emmerik & Wagenaar (1996) discovered that phase relationships between the trunk and pelvis respond to changes in walking velocity, with the movements becoming less in-phase as the velocity increased. Phase relationships have played an important role in establishing how injuries, aging, and disease-induced motor dysfunction impact coordination in human gait. For instance, Hamill and colleagues (1999) found that continuous relative phase in couplings of lower-limb joints were more variable for runners with patellofemoral pain than for uninjured individuals. Phase relationships have been used to show that movement variability in older adults' trunk and pelvic movements were more out of phase in lateral trunk flexion movements, especially at higher speeds, suggesting older adults have less counter rotation in the trunk and pelvis to aid in stability than younger adults (Van Emmerik et al., 2005b). Phase relationships are also an effective means of differentiating gait characteristics between groups experimental subjects with and without Parkinson's disease (Lukšys et al., 2021).

Although studying phase relationships can provide meaningful information about coordination between pairs of joints, ultimately it is not the best choice for studying pianists' coordination characteristics during complex, bimanual piano performance. Studying phase relationships is most effective for characterizing the nature and stability of coordination between two joints at a time. Without extending the analysis by applying methods such as PCA to examine the variability of many phase relationships simultaneously, it can be difficult to characterize multi-joint movement coordination across the body using this approach (Forner-Cordero et al., 2005). Furthermore, it is best applied to the study of repeated movements that can be performed continuously and cyclically, since these movements can be represented by simple functions, like sinusoids. Comparing movements that are sinusoidal allows them to be meaningfully compared in the time domain (Peters et al., 2003), although applying transformations such as Hilbert transforms can produce an analytic signal that can be submitted to phase analysis in some cases (Lamb & Stöckl, 2014). Although many aspects of pianists' movement may be considered repetitive, the timing of joint relationships are often dictated by rhythmic features of the music, which may change frequently in the musical structure of the pianistic task and may not be accurately represented by repetitive functions like sinusoids.

2.2.2 Linear Correlation Methods

A second common approach for assessing coordination is the use of linear correlation methods, which assess the degree to which the variation in one movement variable is linearly related to another (Nelson-Wong et al., 2009). Cross-correlation, developed by Sparrow and colleagues (1987), is a linear correlation method that can be used to compare how well one signal predicts another by shifting one in time in relation to the other to find out which time delay between the two results in the biggest correlation coefficient (Mullineaux et al., 2001). It has been used to compare coordination characteristics between groups of participants, such as individuals with and without low back pain. For instance, Shum and colleagues (2005) found that cross-correlation between movements of the lumbar spine and hip differed between individuals with and without low back pain when participants were putting on socks (Shum et al., 2005). Butowicz and colleagues (2022) used cross-correlation to compare coordination between individuals with and without low back pain who had experienced loss of one lower limb. They found that cross-correlation of data collected from inertial measurement units (IMUs) comparing trunk movements to movements in the ankle, knee, and hip differed between participants with and without lower back pain (Butowicz et al., 2022). Autocorrelation uses a similar approach to cross correlation but instead of comparing two different signals, it compares a signal to itself to investigate the degree to which the signal is self-similar and can be used to predict its own behaviour at future times. Autocorrelation is particularly useful for studying the effects of different conditions on the variability of repeated movement tasks. For instance, it has been used to compare variability characteristics of the movement of individual hands during unimanual and bimanual movement tasks (Torre & Delignières, 2008) and how attention affects the production of bimanual polyrhythms (Peters & Schwartz, 1989). Autocorrelation can also be used to investigate how learning or practice influences movement variability. For instance, Nourrit-Lucas and colleagues (2015) discovered that expert skiers exhibited lower variability overall and longer-range correlations in their movements compared to novices during movements on a ski simulator (Nourrit-Lucas et al., 2015).

Although linear correlation methods are useful for understanding how different time signals are related, they can only be used to compare two variables at a time (Tepavac & Field-Fote, 2001). They do not provide a means of assessing relationships in variation of multiple variables simultaneously, as would be required to describe whole-body coordination characteristics of pianists. Another important limitation of linear correlation methods is that they are only sensitive to linear relationships between variables (Wheat & Glazier, 2005). If variation characteristics exists within a data set that are organized but not linearly distributed, they will not be discovered by linear correlation methods. Sometimes a logarithmic transformation can be applied to non-linear data to linearize it, but this approach is not always successful (Dambolena et al., 2009). In the case of autocorrelation, the movements studied must be repetitive, since the goal of autocorrelation is to find out how consistent repeated movements are over time. The rhythmic variation contained in musical tasks may drive the results of autocorrelation when applied to pianistic tasks, potentially masking participant-specific movement variability.

2.2.3 Non-Linear Approaches Based on Entropy

A growing area of study is the use of non-linear approaches to measure the degree of entropy in a movement or system of movements. Entropy measures are forms of time-series analysis that assess the stochasticity, or randomness, of the variation in a complex system of variables. A chaotic system displays random variation between the variables, making it difficult to predict its behaviour. The more chaotic the variability, the higher the measure of entropy. By contrast, variation in a more deterministic system can be predicted by definable relationships between variables. Systems that vary predictably have lower measures of entropy. Variability is a known feature of the human motor system. Since Bernstein's earliest experiments (Bernstein, 1967) human movement research has continually contended with the inherent variability of the human motor system. According to some theoretical perspectives, movement variability can arise as random output (noise) of the human motor system, manifesting in inconsistent movements (Shea & Wulf, 2005). Research shows that some characteristics of movement variability are associated with lack of practice in early learning, with movement variability decreasing as individuals become more experienced executing a given movement (Schmidt, 1975; Schmidt, 2003). However, research using non-linear approaches has shown that variability itself is neither bad nor good but contains information about characteristics of motor coordination. This theoretical perspective suggests that some types of variability can be a sign of healthy adaptivity within the sensorimotor system (Stergiou & Decker, 2011). In this view, highly deterministic variation is not ideal because it arises from stereotyped movement and reflects a lack of adaptivity in the motor system. However, very chaotic variation can be an indication of lack of motor expertise or the presence of motor control disorders (Stergiou et al., 2006). Some research indicates that variability that is partially deterministic and partially chaotic is optimal for healthy, coordinated, and adaptive movement (Harrison & Stergiou, 2015).

There are several approaches to measuring entropy (sample entropy, approximate entropy, Shannon entropy, and multiscale entropy are just a few) but they all operate on the principle of determining the degree to which previous events in a time-series can be used to predict future events in a time series (Bravi et al., 2011). Entropy measures have been applied to get information about sport performance. For example, using approximate entropy as a measure, Antúnez and colleagues (2012) discovered that experienced tennis players have more lower entropy (more predictable variability) in their serving movements when their serves more accurately hit intended targets (Antúnez et al., 2012). Entropy measures are also used for assessing postural control by analysing variability in centre of pressure measurements (Rhea et al., 2011). For example, Hadad and colleagues (2020) used Shannon entropy to compare variability in the centre of gravity measures of karate experts and expert swimmer conducting one-legged and two-legged stances in eyes open and eyes closed conditions. The karate experts had lower Shannon entropy values than the swimmers in all conditions, suggesting that karate experts have less complexity in postural sway measurements, potentially due to the focus on balance in their physical training. Non-linear measures of variability have even been applied to measure postural sway of musicians. For instance, Demos and colleagues used recurrence quantification analysis and detrended fluctuation analysis to compare the postural sway movements of two trombonists as they played the same solo piece twice in three different performance styles: normal, expressive, and non-expressive (Demos et al., 2014). They discovered that variability in musicians' postural sway is related to variability in the loudness of notes and position in the musical phrase.

The main limitation of entropy measures is that most output a single value measuring the entropy of the system, which must be interpreted based on a chosen theoretical framework, which can vary from study to study (Xiong et al., 2017). The user must contextualize what the degree of randomness says about coordination and movement in the context of their research question. For some areas of study, such as human postural control, the relationships between certain entropy characteristics and healthy postural control are becoming more established (Hansen et al., 2017). However, there is currently no way of assessing what different levels of randomness mean in piano performance. As is suggested by the results of Demos and colleagues in the previously mentioned study on trombonists' postural sway (Demos et al., 2014), it is likely that the level of self-similarity or predictability in the movements of musicians will be heavily influenced by the predictability of the musical pattern. Therefore, the pattern defined by the musical score may have the greatest influence on the entropy measures of pianists' motion capture data, and these measures may not be sensitive to participant-specific coordination characteristics. Another limitation of entropy measures is that they tend to be very sensitive to user-determined input and the length of the data signals (Yentes et al., 2013). Simply changing user-determined parameters or the length of the data signal can vastly alter the results and there are not universal guidelines that can be used to establish appropriate setting for user-determined parameters. There are also many entropy measures to choose from, and it can be difficult to decide which measure is best based on the characteristics of the data (Rhea et al., 2011). Finally, their value is limited in terms of making detailed observations about specific coordination characteristics. In many cases, entropy measures produce only a single number to summarize the nature of many variable interactions. Therefore, it may be better suited to comparing general movement characteristics between contrasting groups of participants. Identifying unique details about individuals' coordination characteristics as we seek to do requires a measurement approach that has more potential for individual variation between participants.

2.3 Principal Component Analysis

Surveying the various approaches previous researchers have used to study coordination characteristics in complex movements lead us to identify Principal Component Analysis (PCA) as a method of analysis that could help identify pianists' unique coordination characteristics and that could potentially be used in future intervention studies assessing somatic methods, such as the Feldenkrais Method®, with musicians. PCA was first developed in 1901 by Karl Pearson (Pearson, 1901) before being further developed by others including Harold Hotelling (1933) and Ian Jolliffe (1972, 1973, 2022). Many fields have adopted PCA as an important tool for detecting independent patterns of variation hidden in complex, multi-variable data systems, such as financial indices (Nobre & Neves, 2019), weather measurements (Azfar et al., 2015), and virus genomes (Wang & Jiang, 2021).

2.3.1 Applications of PCA in the Study of Human Gait

Researchers have found several applications for PCA in the field of human kinetics, such as analysing characteristics of human gait patterns. For instance, a foundational application of PCA to human movement data is Troje's (2002) study of gender-dependent gait characteristics. Using PCA, Troje demonstrated how the dimensionality of complex motion data from human walking could be decomposed into simpler components that could be used to automatically detect movement characteristics associated with a person's gender (Troje, 2002). Daffertshofer and colleagues (2004) demonstrated that PCA could be used to extract principal modes, or principal components, of movement from positional and surface electromyographical data of human gait. Although finding the principal modes of a movement is useful to better understand the general features of the movement, their team also demonstrated that examining the smaller, non-dominant components reveals interesting information about smaller movement details that could be related to unique movement features in an individual or an experimental group (Daffertshofer et al., 2004). Many researchers have applied PCA as a means of comparing movement characteristics between individuals with motor control disorders and healthy controls. For example, Dillmann and colleagues (2014) studied the walking movements of 36 individuals with Parkinson's disease and 35 healthy controls and found that the largest principal component described less of the overall movement variation in those with severe Parkinson's compared to those without at slower and faster walking speeds. The difference in distribution of variance between principal components was also noted for Parkinson's patients with less severe disease, but only at the faster walking speeds (Dillmann et al., 2014). Researchers also used PCA to study variation patterns in lower-limb angles during walking between older adults with a history of falling and older adults with no history of falling (Kobayashi et al., 2014). They found that the fifth principal component contained greater variability related to joint kinematics in individuals with a history of falling compared to those with no history of falling. Verrel and colleagues (2009) used PCA to investigate the effect of increasing cognitive loading in the gait patterns of adults in three age ranges: 20-30 years old, 60-70 years old, and 70-80 years old. They found that gait patterns became less varied with the introduction of a simple cognitive task (counting backward by 1) for all age groups, based on the decreasing residual variance in the PCA. However, as the difficulty of the cognitive task increased, the gait patterns became more regular in the 20-30 group, less regular in 70-80 group, and showed no difference in regularity in the 60-70 group (Verrel et al., 2009). These examples of human gait studies show how PCA can be used to find hidden characteristics in the variation of motion capture data that can signify differences in coordination between experimental groups.

2.3.2 Applications of PCA in Skill Assessment in Sports

PCA has also been applied to assess sport technique in various studies. For example, Federolf and colleagues (2014) used PCA to decompose the movements of six elite junior ski racers into unique sets of individual components to quantitatively compare the individuals' movement. It was found that most principal components were similar across participants, but may have appeared in a different order, meaning that the components accounted for a different percentage of the overall variance for different ski racers (Federolf et al., 2014). Smaller components were more likely to be unique to individuals and could be linked to participant-specific movement features in some cases. The authors suggest that PCA could offer a quantitative way of assessing sport technique that incorporates movement of the entire body, similar to how judges or coaches would observe a movement. Similarly, Young and Reinkensmeyer (2014) used PCA to study variables used by judges to visually assess the quality of dives in competitive high diving. They included 2D kinematic variables related to divers' joint positioning, as well as measures of splash area, and board tip motion in their PCA analysis and found that board tip motion and splash area accounted for more of the variance in the judge's scores than factors related to divers' body positioning (Young & Reinkensmeyer, 2014). These examples show how some researchers have used PCA to develop quantitative means of assessing technique in sport, which has traditionally been done qualitatively.

PCA has also been used to differentiate coordination characteristics between athletes of different skill levels. For example, researchers applied a PCA-based pattern recognition approach to motion capture data from 542 athletes performing seven athletic screening movements (Ross et al., 2018). The models they created using linear discriminant analysis were able to correctly classify 70.66-82.91% of the athletes in the database as either elite or novice, suggesting PCA is statistically sensitive to differences in skill assessment normally conducted through qualitative, visual assessments. Other studies have compared smaller groups of expert and novice athletes in specific sports. For example, Zago and colleagues (2017a) conducted PCA on the motion trajectories of ten expert and ten amateur karateka during the performance of karate forms. Using a second PCA and a linear regression, they were able to find that the principal movements varied as a function of years of experience. They also found that specific features of individual principal components could be used to distinguish the technique of individual karateka, suggesting that PCA could be useful for identifying participant-specific coordination characteristics during complex movement (Zago et al., 2017a). The same research team also used PCA to analyze the movements of six expert and six amateur jugglers juggling three, four, or five balls (Zago et al., 2017b). They were interested in seeing how the juggler's level of expertise and the number of balls being juggled influenced the amount of residual variance (RV) in the PCA (variance explained by the components ranked four or higher). They found that the percentage of variance explained by each principal component varied depending on how many balls were being juggled, with RV increasing with the numbers of balls being juggled. However, the increase in RV was much greater for the amateur jugglers in the five-ball condition, suggesting that the experts had more practiced and regular movement patterns that were not disrupted when adding the fifth ball. By linking individual PCs to certain movement features, the authors were able to deduce movement features of expert juggling that the more amateur jugglers could focus on to improve their skill (Zago et al., 2017b). These studies demonstrate that PCA is useful for discerning differences in movement characteristics between athletes of disparate ability and could help identify movement characteristics that may be associated with different stages of learning from novice to expert.

2.3.3 Applications of PCA in the Study of Musicians' Movement

PCA has also been used in some studies of musicians' movement. For instance, Walton (2016) used PCA to study how different playing conditions, such as the presence of a rhythmic back-track, influenced synchronization in the coordinative features between two improvising musicians. They found that the two musicians tended to move more independently with a rhythmic backing than without. Verrel and colleagues (2013) used PCA to study differences in coordination characteristics of the shoulder, elbow, and wrist joints during cello bowing movements of novice and expert cellists (Verrel et al., 2013). They discovered that novice cellists used a more shoulder-driven bowing strategy, with less movement in the elbow and wrist compared to expert cellists. Gonzalez-Sanchez and colleagues (2019) used PCA to study timing of surface electromyographical signals from the arm muscles of cellists and drummers and discovered participant-specific timing of muscle activation between the more proximal and distal arm muscles (Gonzalez-Sanchez et al., 2019). A few studies have used PCA to study classical pianists' movements. For instance, Tits and colleagues studied component movements in the hand gestures of four pianists of varying levels of expertise as they played a variety of bimanual musical pieces (Tits et al., 2015). They discovered that in general, more component movements were required to explain most of the variation in the data for more experienced pianists, perhaps indicating that hand movements of expert pianists are more varied than less experienced pianists. Furuya and Soechting (2012) used PCA to study how expert pianists' hand gestures responded to changes in tempo during the performance of a series of musical excerpts. They discovered a set of three movement characteristics related to independent finger movement that remained invariant despite changes in the playing speed. Finally, a team of researchers used PCA to study how the timing of nine expert pianists' body movements related to the musical phrase structure in two Chopin Preludes (Buck et al., 2013; MacRitchie et al., 2013). They discovered that some performers' body movements were more associated with larger musical structures, such as the beginning or ending of new musical sections, while others seemed to organize movements based on smaller musical structures within phrases. The content and methods of these studies are reviewed in more detail in articles three and four (chapters five and six) of this thesis.

Of all the methods identified in this chapter, PCA stands out as the analytical approach that allows for quantification of variation in the movement of many motion capture variables simultaneously and shows the greatest promise for providing a means of identifying unique coordination characteristics within individual pianists. Although the PCs identified using PCA of motion capture data cannot point to specific biomechanical features of movements, such as the behaviour of any individual joint or joint system, they possess valuable information about existing structures in the variation of the motion capture data that may researchers may be able to use to identify participant-specific features in the movement variation that point to an individual performer's unique ways of coordinating their body during the performance of a given musical task. PCA-based procedures may provide means of identifying different overlapping sources of variation in the motion capture that could help researchers pin-point variation in the motion capture data related to an individual's unique way of moving. Such variation features could be tracked and measured over time in future studies to determine if they are sensitive to changes in movement coordination brought about by Feldenkrais training. It is possible that studying the variation characteristics illustrated by PCA-based analyses could provide a means of tracking changes to movement that are the result of many subtle changes distributed throughout the body. The purpose of articles three, four, and five of this thesis is to take steps toward developing PCA-based procedures for this application. The next section provides a conceptual description of what PCA does and a simple example of how it can be used to provide information about musicians' movement.

2.4 Explaining PCA: Concepts and Examples

Principal Component Analysis (PCA) is a method based on linear algebra that uses the properties of special linear transformations to matrices to expose the linear relationships that best summarize the variance in a large and complex data set. It can be used as a dimension reduction strategy to highlight which linear relationships describe most of the variance in the data, allowing researchers to examine properties of a simplified data set from which 'extra' variation is removed, or allowing them to remove the most significant components of the variance to look at the variation that is left over. Mathematical descriptions and PCA tutorials for motion capture data are available in several other publications (Daffertshofer et al., 2004; Federolf et al., 2014; Federolf, 2016; Forner-Cordero et al., 2005; Shlens, 2014; Troje, 2002). Since many reading this thesis may have backgrounds primarily in music pedagogy or performance, the following description of PCA gives a simplified explanation, limiting the use of mathematical symbols to help those without a mathematical background engage with the ideas of PCA and to make it easier to understand the explanations provided in other, more detailed tutorials. We present a simple 3D example of PCA applied to a single anatomical marker on a pianists' wrist during a simple playing task to support the mathematical explanations.

2.4.1 A Conceptual Explanation of PCA

Motion capture produces a matrix of trajectories comprised of rows and columns of data. Each column corresponds to a different x, y, or z component of an anatomical marker and each row represents an instance of measurement of the position of the anatomical markers. In a simple motion capture set-up like the one depicted in figure 2.1, the data matrix would contain six columns (three for the x, y, z of the distal ulna and three for the x, y, z of the distal radius) (table 2.1). The matrix would contain as many rows as there were instances of measurement. For our studies, we measured the position of the anatomical markers at a frequency of 100 Hz, or 100 times per second. For instance, five seconds of data collection would result in a matrix of 500 rows.

Figure 2.1

Anatomical Markers on the Right Distal Ulna and Right Distal Radius

Table 2.1

Sample Matrix of Motion Capture Data During a Simple Piano Task: Right Distal and Ulna Right Distal Radius

Radius-X	Radius-Y	Radius-Z	Ulna-X	Ulna-Y	Ulna-Z
1.6	0.9	-0.5	1.8	1.1	-0.8
1.7	0.9	-0.6	1.9	1.2	-0.8
1.8	0.9	-0.6	2.0	1.2	-0.9
1.9	1.0	-0.7	2.0	1.2	-1.0
2.0	1.0	-0.7	2.1	1.2	-1.0
2.0	1.0	-0.8	2.2	1.2	-1.0
2.1	1.0	-0.8	2.2	1.2	-1.1
2.1	1.0	-0.8	2.3	1.3	-1.1
2.2	1.1	-0.9	2.3	1.3	-1.1
2.3	1.1	-0.9	2.4	1.3	-1.1
⇓	⇓	⇓	⇓	⇓	⇓

Note. All measurements are in millimeters. Complete matrix has 9,881 rows of data.

In the mathematics of linear algebra, algebraic principles many will be familiar with from high school education are applied to large matrices of numbers rather than to single algebraic expressions. Linear transformations involve applying simple mathematical processes, such as addition, subtraction, and multiplication, to entire matrices of numbers. PCA capitalizes on the special properties of certain kinds of linear transformation of a data matrix. The first step is to standardize the variables so that variables with larger magnitudes do not overwhelm variables with smaller ranges in the subsequent calculations. This is usually done by calculating the mean of each variable and subtracting the mean from each measurement of the variable.

The next step is to calculate the covariance matrix of the data set. A detailed description of how to calculate a covariance matrix can found in other literature (Daffertshofer et al., 2004). Conceptually, a covariance matrix computes the covariance between each possible pair of variables within a data set to get a measure of how much two variables do or do not vary together, typically using a sum of squares approach. This involves subtracting the mean of a variable from each measurement of that variable in the data set. Corresponding pairs of measurements are multiplied together at each time, and then all the resulting products are added together. This summation is then divided by n-1 (one less than the total number of measurements) to get the covariance between the two variables in the pair. A positive covariance means that the variables increase and decrease together. A negative covariance means that as one variable increases, the other decreases. Higher absolute values of the covariance indicate a stronger relationship. This process is repeated for every possible pair of variables, and the results are organized in a square matrix that has the same number of rows and columns as there are variables in the system. For example, if we only consider the x, y, and z data from the right ulna in table 2.1 (the last three columns), there would be three variables, resulting in a 3 x 3 covariance matrix. The covariance matrix is symmetrical, meaning that it has the same values reflected along the diagonal. A visual representation of a covariance matrix using the three-variable system of a single marker on the right ulna is presented in figure 2.2. Entries of the same colour have the covariance value because they compare the same pair of variables, producing the symmetric property of the covariance matrix. The entries in black, on the diagonal, are technically variances, not covariances, of the variables themselves, because they compare each variable to itself.

Figure 2.2

Visual Representation of the Properties of a Covariance Matrix

	Right Ulna, x	*Right Ulna, y*	*Right Ulna, z*
Right Ulna, x	***Cov(x,x)***	***Cov(x,y)***	***Cov(x,z)***
Right Ulna, y	***Cov(y,x)***	***Cov(y,y)***	***Cov(y,z)***
Right Ulna, z	***Cov(z,x)***	***Cov(z,y)***	***Cov(z,z)***

The next step in PCA is to compute the eigenvectors and eigenvalues of the covariance matrix. “Eigen” means “special” in German, and eigenvectors refer to a special set of vectors that have a unique property. When a covariance matrix is multiplied by its set of eigenvectors, the result is the same as if the eigenvectors were multiplied by scalars, called eigenvalues. The equation displaying this relationship is as follows (figure 2.3):

Figure 2.3

Eigenvector and Eigenvalue Relationship with Covariance Matrix

$$\underbrace{A}_{\text{A = covariance matrix}}\overbrace{X = X}^{\text{X = eigenvectors}}\underbrace{\Lambda}_{\Lambda\text{ = eigenvalues (on the diagonal)}}$$

In this equation, the covariance matrix (calculated from the data matrix) is represented by 'A', which appears on the left side of the equation. On the left and right side of the equation, the letter 'X' represents a matrix of eigenvectors (each column is an eigenvector). There will be an eigenvector column for each variable in the data matrix, and each eigenvector of the covariance matrix will have as many elements as there are variables. On the right, Λ represents a diagonal matrix with scalars (numbers with magnitude, but not direction) on the diagonal. This equation describes a special situation in which the linear transformations applied by multiplying the eigenvectors by the covariance matrix produces the same results as merely scaling the eigenvectors by multiplying by the corresponding eigenvalues.

It is possible to compute the same eigenvectors and eigenvalues by directly analysing the measured data using a method called singular value decomposition (SVD). This involves a different set of linear transformations which are well documented in other literature (Golub & Van Loan, 2013). When the SVD approach is used, a set of vectors is generated called the principal components and a weighting matrix is created that allows the data to be reconstructed based on the variance described by the PCs. The weighting matrix can be thought of as ratios that describe "how much" of each principal component is contained in each variable within the data set. This allows for the reconstruction of the original data according to the variation described by the eigenvector (henceforth referred to as the PC vector). The eigenvalues of the covariance matrix indicate the amount of the total variance contained in each of the principal component vectors.

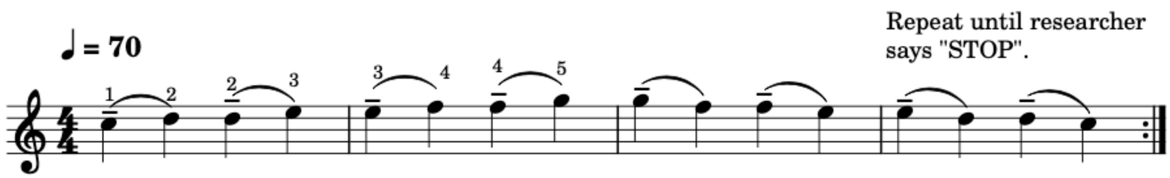
PC vectors have interesting properties that relate them to the variance in the original data set. PC vectors are linearly independent and each one is perpendicular to the others. Typically, PCA ranks all PC vectors in ascending order according to the amount of variance they explain in the data set, with principal component 1 (PC1) describing the greatest proportion of the variance, PC2 describing the second greatest proportion of the variance, and so on until there are as many PCs as there are variables in the data set. In our simple, three variable example of the x, y, and z trajectories of the right ulna marker, there would be three PC vectors (three columns).

2.4.2 Example of PCA Applied to 3D Motion Trajectories of a Single Marker on a Pianist's Wrist

To help visualize the kind of information PCA gives about variation in data sets, we present the following three-dimensional PCA example on the x, y, and z motion capture trajectories of the right distal ulna marker only during a pianists' performance of a simple, two note slur exercise, depicted below in figure 2.4. The pianist repeated the exercise seven times without stopping.

Figure 2.4

Two Note Slur Exercise for the Right Hand



First, we plotted the raw motion capture trajectories of the x, y, and z right distal ulna on a three-dimensional plot to visualize the spread of the data. The raw trajectories are plotted in three-dimensions in figure 2.5. Figure 2.6 displays separate plots of the x, y, and z motion capture trajectories of the right distal ulna. We can observe from the raw data plots that much of the movement variation takes place in the z-axis, with the wrist moving up and down vertically in relation to the piano. This is not surprising, since the task requires the pianist to move their wrist up and down when connecting pairs of notes. The hand is constrained to a location of five consecutive notes on the piano, so it does not have to move a great deal horizontally along the keyboard (x-axis). The wrist moves slightly forward and backward parallel to the lengths of the keys (y-axis).

Figure 2.5

3D Raw Motion Trajectory (X, Y, Z) of the Right Distal Ulna Plotted in Three Dimensions (cm.)

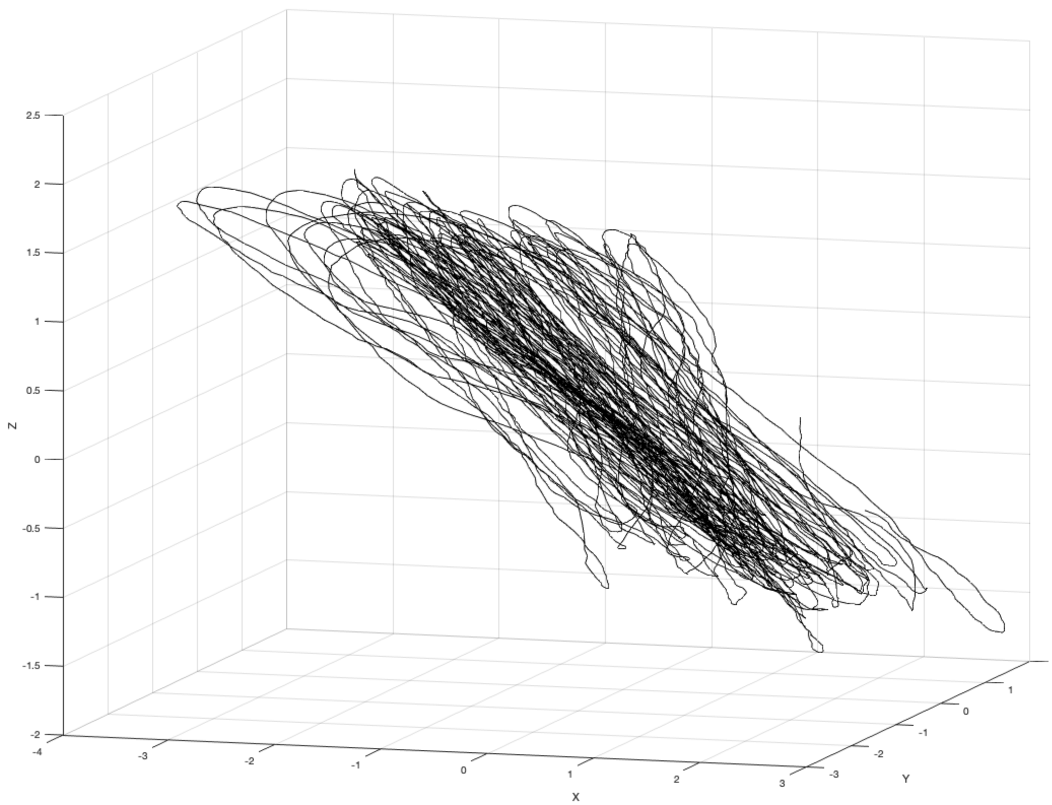
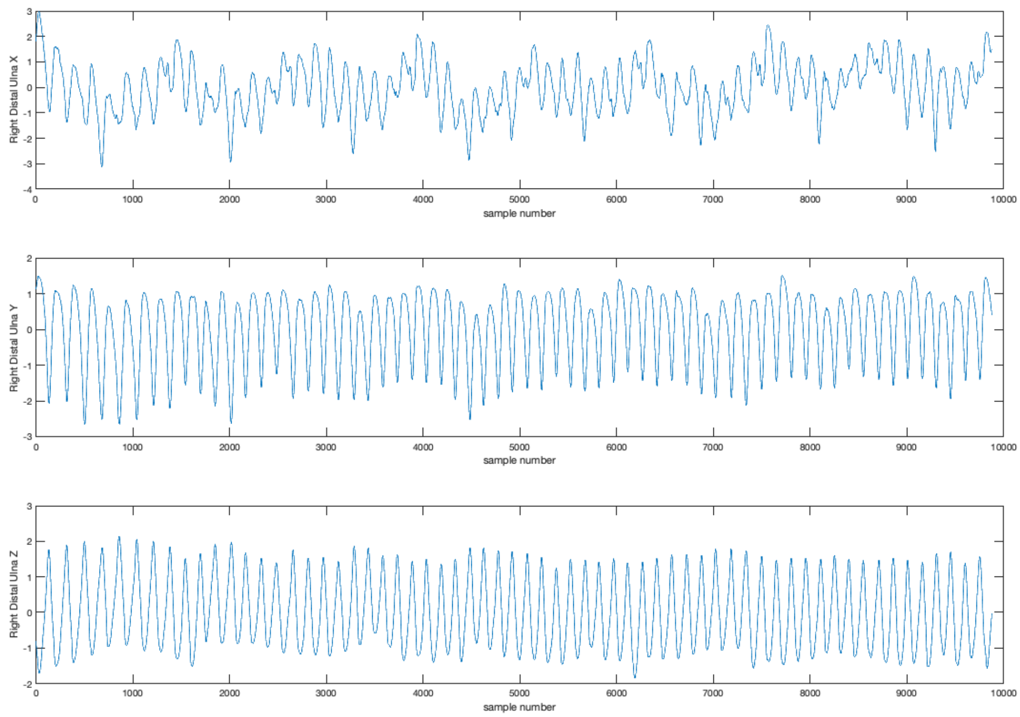


Figure 2.6

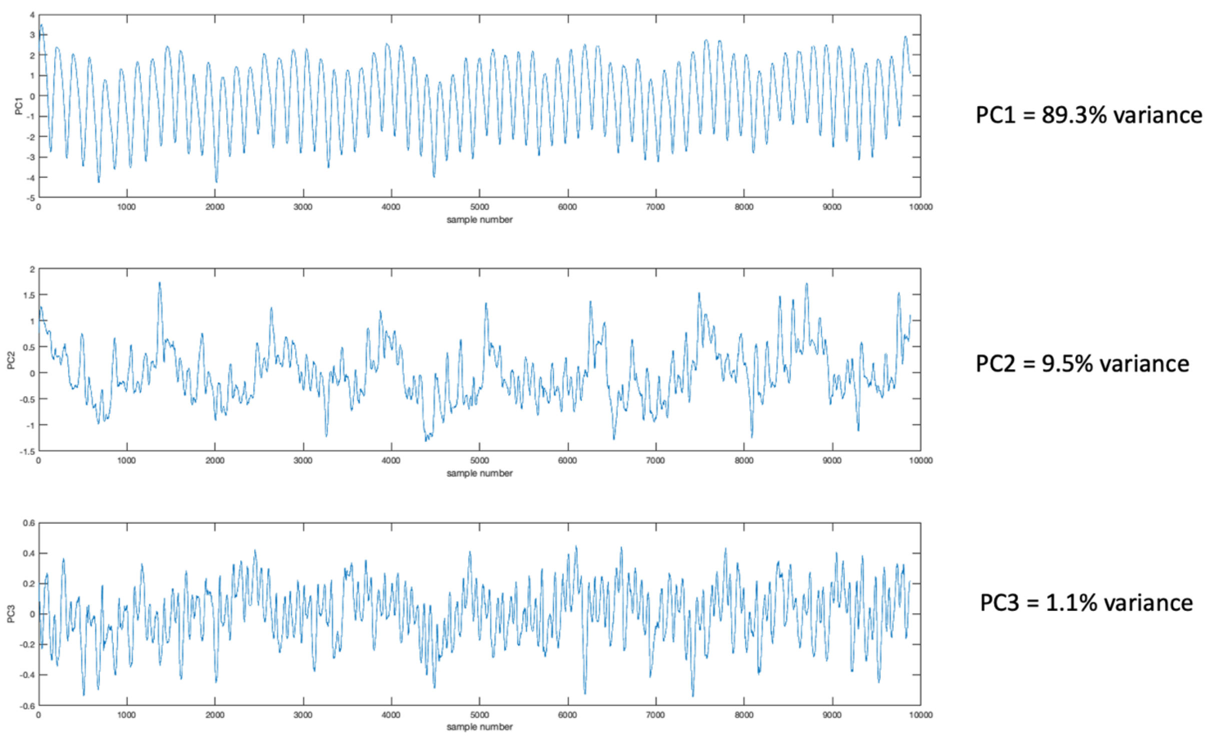
Separate Raw Motion Trajectories (X, Y, Z) of the Right Distal Ulna Plotted in Three Dimensions (cm)



Next, we ran a PCA analysis on the data matrix (9881 rows x 3 columns) using the built-in MATLAB function. Since there are three variables in the matrix, it results in three PCs. Figure 2.6 plots the three resulting PC vectors individually. These vectors represent variation in the data, and have no measurement unit, hence the lack of a y-axis title. The x-axis corresponds to the sample number. As shown in figure 2.7, PC1 accounts for 89.3% of the overall variance, PC2 accounts for 9.5% of the overall variance, and PC3 accounts for 1.1% of the overall variance. This means that most of the variation in the data can be summarized by the linear relationship described by PC1. It is important to note that the variance represented by individual PCs cannot be linked to specific variables directly. Each PC contains information about how all the variables interact. In the case of motion capture data, a PC represents a relationship between variables, not a specific movement or anatomical feature.

Figure 2.7

Plots of PC1, PC2, and PC3 from the PCA on the Right Distal Ulna



The PC weightings are contained below in table 2.2. Multiplying PC1 in figure 2.7 by column 1 in table 2.2 reconstructs the original data set according to variance described by PC1. All variance perpendicular to that PC vector is removed. Similarly, multiplying PC2 in figure 2.7 by column 2 in table 2.2 reconstructs the original data set based on PC2, which is independent (perpendicular to) the variance described by PC1. Multiplying PC3 in figure 2.7 by column 3 in table 2.2 reconstructs the original data set based on PC3, which is a third independent relationship, perpendicular to PC2 and PC1. Reconstruction of the data according to these PCs results in three perpendicular vectors, which can be plotted in three dimensions, as shown in figure 2.8. PC1 is depicted in blue. It is the longest and represents the most variance in the data set. PC2 is perpendicular to PC1, depicted in red. PC2 is the second longest and represents the second greatest proportion of the overall variance. PC3, depicted in green, is the shortest, and represents the least amount of overall variance in the data.

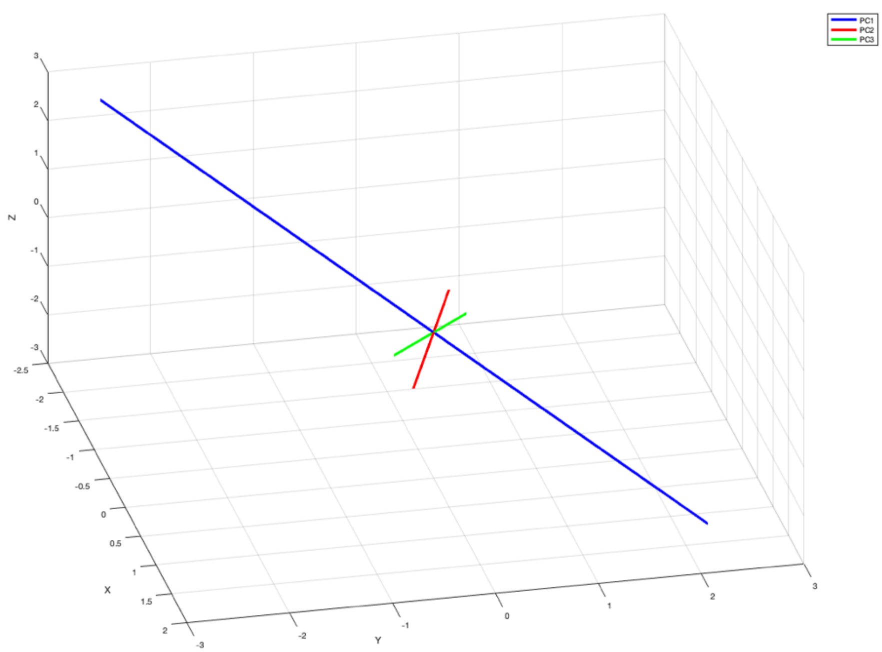
Table 2.2

Weightings Corresponding to Each PC from PCA of Right Distal Ulna

PC1 Weightings	PC2 Weightings	PC3 Weightings
0.546128779	0.837266168	-0.026994838
0.593704151	-0.36412292	0.717586149
-0.590981166	0.407921394	0.695946404

Figure 2.8

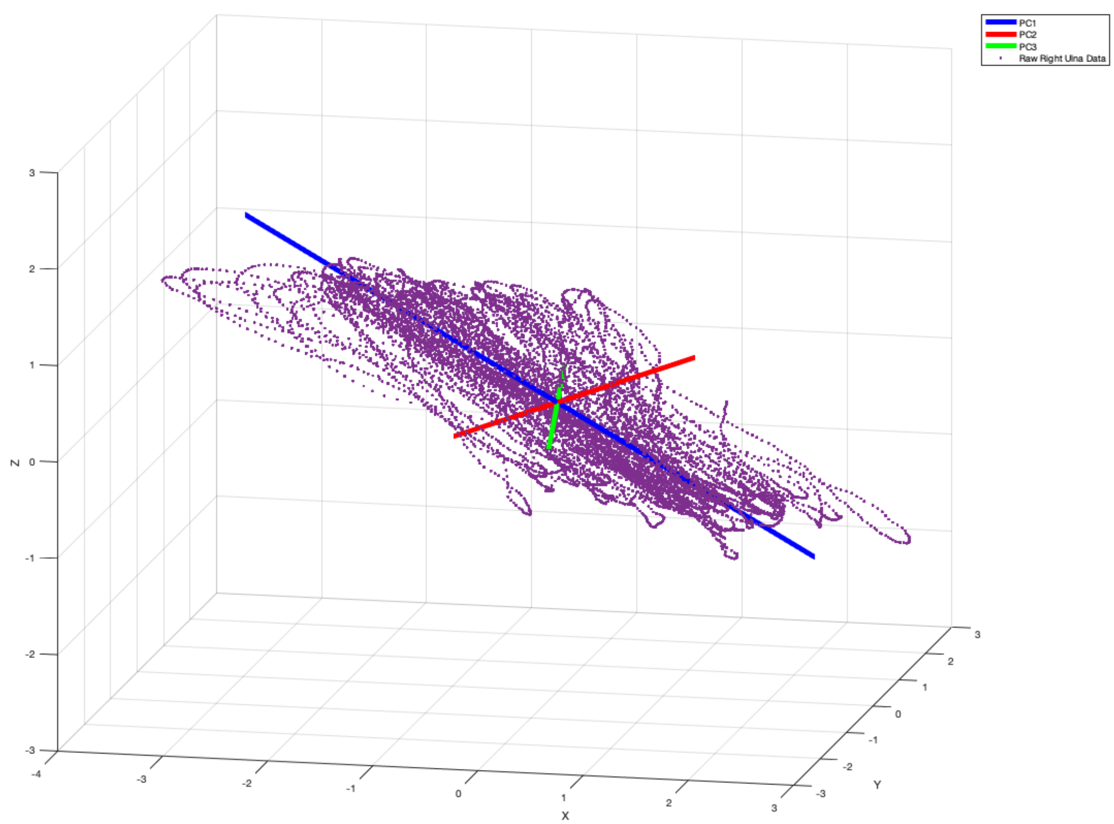
Independent Linear Variation Relationships Represented by PC Data Reconstructions for the Right Distal Ulna (cm.)



Superimposing the linear PC data reconstructions in figure 2.8 onto the raw 3D motion capture data depicted in figure 2.5 illustrates how the PCs can be used to reconstruct independent, linear lines of best fit within the data set, each representing an independent linear variation relationship among the data points. In figure 2.9, the raw data has been plotted with purple points rather than lines as in figure 2.5 to aid in the visibility of the PC lines.

Figure 2.9

Linear PC Reconstructions Plotted as Lines of Best Fit in the Original 3D Data (cm.)



The relationship between the PCs and the variation in the data are easy to visualize in a three-dimensional example such as the one presented here. However, motion capture data sets with multiple anatomical markers have a much greater dimension. In our work, the matrix will have 66 columns, (three cartesian directions (x, y, z) multiplied by 22 anatomical markers). This means the PCs will be describing linear variation relationships in 66-dimensional space and cannot be visualized in three-dimensions like the previous example. However, the concepts are the same in any dimension. Each PC represents a fundamental aspect of movement variation within the data set. The first PC always accounts for the most variation, and the each subsequent one accounts for less. In 66 dimensions there will be 66 PCs. However, in practice, most of the smaller PCs account for so little variance that they are negligible. Many studies only include the PCs required to describe a certain threshold of variance, such as 90% (Forner-Cordero et al., 2005; Warmenhoven et al., 2019; Zago et al., 2017a; Zago et al., 2017b). In our study, we usually include PCs describing two percent or more of the variance, unless otherwise stated. We chose the threshold of two percent because we found evidence of patterns related to the musical tasks and participant movements in PCs around two-percent variance, and we could be confident they were not attributable to noise or random variation. Articles 3, 4, and 5 of this thesis explore how PCA can be applied in 66 dimensional space to better understand unique variation characteristics in pianists' motion capture data.

2.5 Conclusion: Strengths and Limitations of PCA as a Means of Measuring Pianists' Coordination Characteristics

Comparing PCA to the other methods of analyzing coordination features in complex motion data reviewed in this chapter demonstrates that PCA is a promising tool for gaining insight into participant-specific coordination characteristics of pianists. The examples of research using PCA to study human movement in different contexts demonstrate the suitability of the approach for assessing relationships from many movement variables simultaneously. The results of the studies reviewed in this chapter illustrate how PCA is not only useful for assessing the primary variation characteristics present in movement data but can also be used to examine movements accounting for less of the variance that may be more closely related to participant-specific characteristics or potential markers of movement expertise. We propose that PCA could provide a means of identifying participant-specific variation characteristics in the motion capture data that could be used to create participant-specific variation profiles related to their unique ways of moving. These variation profiles could be tracked over time to assess the impact of somatic methods, such as the Feldenkrais Method®, on pianists' movement characteristics. Such a tool would be particularly suited to single-subject design structures in which individual participants are followed for extended periods of time before, during, and after a movement intervention.

It is important to remember that PCA is not itself a means of measurement, but a means of transforming a data set to examine it based on the variation characteristics between the variables. As discussed in the section on non-linear measurements and entropy, when it comes to studying human movement, variation is neither inherently good nor bad, and the meaning of variation characteristics must always be interpreted based on a theoretical framework and an understanding of the different factors that influence variation in a data set. On its own, PCA cannot discriminate between different sources of variation in a data set. The authors of the various studies reviewed in this chapter have used various approaches for connecting PC characteristics with specific movement attributes, such as examining the relationship between the weighting matrix and individual PCs. However, since each PC contains information from all the data, it is generally impossible to link individual PCs with individual movement variables. Part of developing PCA-based tools for creating participant-specific variation profiles will require researchers to develop frameworks for identifying and classifying the different types of variation contained within the motion capture data of performing pianists.

Articles three, four, and five of this thesis explore these strengths and limitations of PCA in the context of studying pianists' motion capture data collected during the performance of various musical tasks. Article three begins by exploring the sensitivity of standard PCA to participant-specific differences in pianists' coordination characteristics in pianistic tasks of varying levels of complexity. Article four takes a more detailed assessment of the characteristics of PC waveform shapes to assess different sources of variation contributing to the motion capture data of pianists, informing the development of a theoretical framework to aid in interpreting the types of variation contained in the data to help plan PCA-based procedures for targeting participant-specific variation characteristics. Article five proposes a new method of analyzing the results of PCA that provides insight into both task-determined and participant-specific coordination characteristics of pianists.

CHAPTER 3: ARTICLE 1

The Feldenkrais Method for Musicians: Addressing the Need for Objective Measurement

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CHAPTER 6
THE FELDENKRAIS METHOD FOR MUSICIANS: ADDRESSING THE NEED FOR OBJECTIVE MEASUREMENTS

Jillian Beacon, Gilles Comeau and Donald Russell

Carl Czerny wrote that 'the movements of the body have so great an influence on piano-forte playing, that a good and graceful position must be the first thing to which the pupil's attention should be drawn'.[1] The notion that poised and erect posture is essential to piano playing persists in pedagogical traditions today. Somatic training approaches such as the Feldenkrais Method (FM) offer strategies that can help musicians move beyond static ideas about posture to develop a more nuanced and dynamic understanding of how habits of body use influence the ability to play freely and expressively. Many musicians claim that FM has helped them recover from playing-related pain (PRP) and go on to play better than ever before.[2] These claims have increased awareness of FM in music education, leading to its incorporation in prestigious music training programmes around the world. However, at present, access to FM in music education is not widespread, with access largely limited to elite training schools or special programmes in workshop settings. With the high prevalence of PRP among both professiona1[3] and pre-professional musicians[4] well documented in research, music educators require access to more effective strategies for helping their students remain healthy throughout their study.[5] It is urgent that experts in somatic modalities like FM find ways to include their perspectives in the academic and administrative conversations taking place about how to better address musicians' health and well-being.

An important and currently lacking part of this conversation is scientific research that not only offers objective evidence of FM outcomes for musicians, but also investigates the neurological and physiological mechanisms underlying the Method's perceived benefits. Although a plethora of anecdotal evidence is available in the form of testimonials and practitioner-reported case studies, the body of research on somatic training is small, with very few studies on musicians. If FM is capable of helping musicians play and feel better, high-quality research studies can highlight its strengths and reveal its limitations. A body of scientific literature on FM outcomes for musicians could increase music educator's knowledge about the Method and facilitate greater trust in its techniques. This knowledge would help educators make informed decisions about incorporating FM into evolving pedagogies concerning musicians' health that increasingly emphasize body awareness. Musician-centred research would also help FM practitioners learn how their techniques could best be adapted to help musicians in the contexts of practice and performance.

The goal of this chapter is to help orient future researchers towards methodologies that will contribute empirical research on FM and musicians. It addresses the need for objective measurement of musicians' motor behaviour in response to somatic training methods such as FM, focusing on pianists. Our discussion pertains to research on physiological measurements of body-positioning and movement without extending to psychological outcomes or assessments of performance quality. The first section reviews literature on how somatic methods, including FM, have been researched so far with both musicians and non-musicians. The second section discusses the strengths and limitations of various biomechanical approaches for measuring body-positioning for FM research, with the goal of helping researchers choose the best methods for their own research questions. The chapter closes with a discussion about the unique challenges of choosing variables representing movement behaviour that respect the learning theories and teaching techniques that make FM unique.

Evidence of somatic training outcomes for musicians

Musicians were one of the earliest groups to recognize how Feldenkrais's Awareness through Movement (ATM) or Functional Integration (FI) lessons could benefit them as artists. In ATM, students actively explore movements based on verbal directions given by the practitioner, and the classes are often done in groups. These lessons seek to create a comfortable and safe context for individuals to become aware of subtleties in sensations and movement quality as they explore variations in patterned movements. Students are encouraged to approach the movements non-performatively, focusing on the quality and ease of the experience, rather than the 'correctness' of execution. The goal of ATM is to help students' nervous systems learn to seek out movements which are more comfortable, efficient or adaptable, rather than persisting in familiar patterns which may limit motor dexterity or contribute to discomfort. During an FI lesson, students experience a one to-one interaction during which the practitioner gently moves the student's body while they are recumbent. Practitioners seek to move the student in ways that seem comfortable and familiar to them rather than forcibly manipulating the body through stretching, pressing or pulling. It is theorized that as the practitioner joins the student's existing movement tendencies, habitual patterns of muscular tension release as the work of the muscles is overtaken by the support of the practitioner. The Method seeks to work with, and not against, the nervous system's preferred patterns of motor behaviour so that new movements introduced by the practitioner are experienced as simple, pleasurable and congruous with the person's sense of themselves. 'The benefits of FM in music performance have been documented anecdotally, with many musicians testifying to improvements to musculoskeletal pain[6] or performance anxiety[7] through exploration of Feldenkrais FI and ATM lessons. Intriguingly, many musicians also attest to more elusive improvements in musical expressivity and technical control. It is common for students to report an increased sense of well-being or that their playing seems to improve even after only short-term exposure in workshop scenarios. For example, Scotty Barnhart, trumpet player and director of the Count Basie Orchestra, had the following to say in a YouTube interview after receiving two Feldenkrais lessons for the first time from practitioner Alice Boyd for a PBS documentary: 'I feel a whole lot better. I am energized and I feel alive. Things I didn't know I was doing wrong she fixed! So, now I am standing up more on the balls of my feet. My body is aligned a whole lot better. I am breathing easier, and it is just easier to play.'[8] Qualitative descriptions of improvements to musicians' musculoskeletal pain symptoms are also common. For instance, Nelson[9] presents a descriptive case study of a female violinist suffering from debilitating neck pain at the Eastman School of Music. Nelson documents her progress, describing how after seven Fl lessons her neck pain no longer bothered her in regular playing situations and she felt that her playing had improved overall.

Testimonials and practitioner-reported results such as these are invaluable because they convey pertinent details about individual experiences and document the process and outcomes of FM from the perspectives of practitioners and their students. However, they do not constitute research-based evidence from a scientific perspective. Student accolades and practitioner reports of best-case scenarios could be susceptible to bias, and often contain vague descriptions of qualitative experiences that are difficult to measure quantitatively. Although descriptive case-study reporting should continue, researchers can now begin using information from testimonials and descriptive case studies to formulate and scientifically investigate hypotheses about specific mechanisms underlying the more general positive effects reported by students and practitioners using objective measurement.

Scientific research on the Feldenkrais Method

Most research on FM has investigated its suitability as an intervention for musculoskeletal pain. Comprehensive reviews of research studies on FM, including those investigating musculoskeletal pain, can be found in a review published by Jain and colleagues, [10] and systematic reviews by Ernst and Canter,[11] and Hillier and Worley.[12] These reviews suggest that although almost all studies on FM report positive outcomes from participation in the Method, methodological limitations, including high potential for bias, small sample sizes, lack of baseline testing and use of unverified measures, prevent definitive conclusions being made about FM as a treatment for various musculoskeletal disorders based on the data available at this time. Although research results about the impact of FM on pain symptoms are ambiguous,[13] some studies suggest that FM may help improve patients' self-efficacy for pain management when compared to traditional physiotherapy treatments.[14] The reviews indicate that researchers studying FM have struggled to meet the demands of randomized controlled trials (RCTs), citing difficulty in recruiting a sample of participants of ample size and homogeneity to permit statistical analysis of the results. In addition, RCTs are unable to capture the diversity of individuals' responses to FM lessons, since RCT methodology necessitates the selection of discrete dependent variables which can easily be compared between large experimental and control groups. Many practitioners worry that this approach risks misrepresenting the Method by reducing it to discrete, generalizable outcomes and overlooking the potential for individual variation which is central to the Method.

Objective measurements of musicians' body-positioning and movement

An alternative to studying the impact of FM on subjective experiences such as participant reported pain or functionality could be to measure motor behaviour using motion-tracking technology. This approach has not yet been pursued in music research, but it may offer practical solutions to the problems posed by large-scale studies on subjective measures. The primary objective of most somatic methods is to influence biomechanical functioning by disrupting habitual patterns of motor behaviour, or 'self-use'. This is especially true of FM, which purports to help students learn about themselves using practitioner-directed and student-directed movement as a platform for exploratory, sensorimotor learning.[15] By bringing awareness to movement, the Method seeks not only to change a person's habits of movement, but in doing so also change how they experience their entire self.[16] Therefore, it could be posited that any positive benefits musicians may incur from the Method regarding pain or performance quality could be linked to observable changes in motor behaviour, which could be objectively measured by researchers given the appropriate tools. Assessing the impact of somatic training on variables relating to body-positioning and movement of musicians seems like a logical next step in research, especially considering that somatic practitioners routinely use visual assessments of body-positioning and movement as an aspect of their teaching.

A few pioneering studies can be found that quantitatively measure the impact of somatic methods on movement and postural biomechanics, primarily in non-musicians. For instance, Kutschke measured the neck and shoulder postural alignment, range of motion and muscle activity in healthy people after participating in twenty Alexander Technique sessions over eight weeks. Surface electromyogram (sEMG) measurements from this study indicate that muscle activity in the neck and shoulder altered after the Alexander training, and that measurements of forward head posture improved significantly for the intervention participants, especially during sitting and typing.[17] Other studies have found evidence that patterns in postural muscle recruitment are altered in individuals trained to teach Alexander Technique.[18] These studies provide evidence that long-term exposure to somatic training could impact motor control strategies for posture, and suggest further study on patterns of muscle activation is warranted with FM.

There are also some first examples of studies on the impact of somatic training on musicians that include assessments of posture and movement. These include the studies on music performance quality and body use of instrumentalists by Valentine and Williamon,[19] and Wong,[20] which both incorporate posture quality rating scales to examine practitioner-reported differences in musician posture characteristics from before and after somatic training interventions. The study by Valentine and Williamon randomly assigned eighteen musician participants (consisting of wind players, string players, keyboardists and singers) to receive thirty-minute Alexander lessons once a week for 12 weeks (n=10), or to undergo ten sessions of neurofeedback training over 6 to 8 weeks (n=8). Researchers video-recorded musical performances from before and after the training, and the videos were randomly ordered and assessed by experts external to the college. The experts rated the posture of the musicians before and after the interventions using a rating scale developed by the practitioner conducting the lessons in the study. scale examined ten categories of The Alexander Technique movement and posture goals, including 'head-neck-back' relationship and 'upper-limb/back'. It was found that the Alexander Technique participants demonstrated improvements in seven out of ten categories of the Alexander Technique movement and posture goals when compared with the neurofeedback participants• The clearest improvements in posture were noted in the singers in this study.

In the study by Wong, ten pianists were assigned to undergo a fifty-minute Feldenkrais' Body Mapping or Alexander Technique lesson. A panel of eight somatic training practitioners rated the 'body usage' of participants in the video recordings of participant performances of scales, Beethoven's Für Elise, and Schumann's Wilder Reiter from before and after the somatic training interventions. The researcher developed a seven-point Likert scale that required raters to assess the quality of body usage in the head/neck, shoulders, arms, torso, legs and feet from 'very good usage and coordination' to 'severe misusage'. Statistically significant post-somatic improvements were only noted for head and neck usage, although raters tended to rate body usage as slightly better in the post-somatic lesson videos for the other areas of the body as well.

These two studies are important because they are the first examples of scientific evidence that somatic training can impact playing posture in musicians. However, research has called into question the validity of visual assessment scales as tools for reliably measuring posture in scientific research.[21] Visual assessments of posture tend to have a poor inter- and intra-rater reliability; measurements are often not highly repeatable between different measurers using the same scale, and measurements can fluctuate within the same measurer from day to day.[22] Assessment instruments like postural rating scales must be assessed for reliability and validity to be considered scientifically valid.[23] Evidence of this validation process is lacking from existing studies on somatic education with musicians. This illustrates a need for more objective measurement tools when assessing aspects of body-positioning or movement quality.[24]

As of yet, no studies with musicians have used objective measurement tools to quantitatively measure posture and movement from before and after somatic training. Lee and colleagues have demonstrated the feasibility of this approach in their kinematic analysis of a cellist and flautist before and after an eight-week training programme involving yogic breathing and physical therapy exercises.[25] Feldenkrais researchers could use a similar approach and employ motion-tracking tools, such as optical-based motion-capture systems or video-based motion tracking software, to collect quantitative data on how musicians' movement strategies evolve with FM experience. The next section presents possible methods of objectively measuring body-positioning and movement for this purpose, assessing the benefits and drawbacks of each approach in the context of research pertaining to FM and musicians. The discussion considers different analytical approaches for defining posture and movement variables from data acquired using motion-tracking technology.

Quantitative measurement of instantaneous body-positions

One biomechanical approach for objectively examining the physiological impact of FM is to take instantaneous measurements of body-positioning to quantify joint angles and alignment of anatomical locations at specific points in time. This approach involves taking photos with a camera or tracking motion with an advanced optical system and either choosing specific points in time to take measurements or taking an average of multiple measurements. Researchers using this method must choose which parts of the body will be measured, which strategies will be used to assess the quality of the positions and how data will be selected for analysis. Markers must be placed on relevant anatomical landmarks so that their positions can be tracked and distance and angle measurements can be taken.

Plumb-line approach

Since many somatic practitioners are concerned with alignment of points of balance in the head, shoulders, and spine, hips, knees, and ankles,[26] and since poor postural alignment in these parts of the body is frequently cited as a factor in the development of playing-related musculoskeletal disorders (PRMDs)[27] researchers may wish to examine vertical alignment of these points to investigate somatic training outcomes with pianists. Traditionally, vertical alignment in these parts of the body has been assessed against plumb lines to check if important structural joints are vertically arranged in such a way that the body can balance freely. This principle is frequently used in chiropractic, physical therapy and somatic training assessments, and has been used as a criterion for assessing posture quality in resting positions in research.[28] Plumb-line approaches to posture measurement rest on the assumptions that vertical alignment and postural symmetry represent postural ideals that are associated with musculoskeletal health. However, the usefulness of straight plumb lines as diagnostic criteria for posture has been questioned, and evidence shows that the points of balance at the ear, shoulder, hip, knee and ankle are not generally arranged in a straight vertical line in standing positions in healthy subjects.[29] Postural symmetry in the right and left sides of the body in the anterior and posterior views is also occasionally used as a standard representing postural health for diagnostic purposes. However, research demonstrates that asymmetry in the resting positions of the pelvis, shoulder and trunk is normally observed in healthy, pain free individuals, raising questions about the use of symmetry as a baseline criterion for good posture.[30] Researchers should consider the variability of healthy posture when using straight plumb lines or lines of symmetry, and consider complementing the data with alternative forms of posture measurement and assessment. This is particularly true for Feldenkrais research, since FM does not actively seek to promote symmetry in positioning, but rather draws attention to asymmetry in positioning and function as a learning tool for promoting greater acuity in self-awareness.

Strategies for measuring head, shoulder and spine position

Since it is expected that the resting muscle tonus of postural control muscles will change as a result of FM lessons, researchers may be interested in examining key postural relationships for evidence of change in patterns of muscular activation. Researchers have devised different approaches to measure head, shoulder and spine positioning that could be useful in some FM research contexts. For example, forward head position is frequently measured as the angle formed between a line passing from the C7 vertebra through the ear tragus, and a horizontal line passing through C7 in the sagittal plane, while an individual is sitting or standing. Similarly, the angle formed between a horizontal line passing through the ear tragus, and the line connecting the ear tragus and the outer canthus of the eye have been used to assess the angle of the head at the atlas occipital joint.

Shoulder position is occasionally determined by measuring the horizontal and vertical displacement of a point on the shoulder in relation to the C7 joint to measure whether the shoulders are elevated or rest substantially forward from the body.[31] Other researchers have measured the angle between the line connecting a point on the shoulder and the C7 vertebra' and a horizontal line extending forward from the shoulder in the sagittal plane to represent the degree of forward shoulder posture.[32] Methods for measuring spine curvature vary widely with different vertebrae chosen as landmarks from study to study.[33] Since measurement procedures for posture of the head, shoulders and spine have not been standardized, it is difficult to compare results across different studies examining similar postures. This means that researchers interested in measuring the impact of somatic training on pianists' posture must design their own measurement protocols according to their own needs and expertise.

Selecting posture variables for research on somatic training for pianists

Reports on changes to posture and movement as a result of somatic training are often descriptive, or non-specific, and understandably vary among individuals, making it difficult for researchers to choose specific parts of the body to measure when looking for meaningful changes in the context of piano playing. Since research has shown a connection between forward head posture and musculoskeletal pain in the neck in computer users, this position could be a good choice for measurement with pianists. However, researchers should be cautious about extending conclusions from research on computer users to pianists, since the two activities place different biomechanical demands on the upper body.

Although research associating elevated or forward shoulder positioning with musculoskeletal pain is not conclusive, piano teachers are often concerned about the elevation of shoulders during performance, since it might be an outward indication of excess tension or performance anxiety. Evidence does suggest that there is a correlation between having protracted shoulders and forward head position and incidence of musculoskeletal pain in musicians.[34] Therefore, researchers could consider measuring the vertical and forward displacement of the shoulders in respect to the spine and position of the head in relation to the torso as posture variables pertinent to piano playing.

Extreme angles of spine curvature held statically at length have also been implicated as problematic in the posture of musicians, warranting research on the impact of somatic training on the vertebral positioning and spine curvature of pianists.[35] Investigating these three regions of the body (the head, shoulders and spine) would give a comprehensive overview of the vertical postural alignment of performing pianists, allowing researchers to examine if FM lessons impact performance postures of the head and torso.

The challenge of assessing posture quality

Some studies suggest specific postural characteristics put musicians at greater risk for developing musculoskeletal pain.[36] It may therefore seem straightforward to simply measure whether FM helps pianists avoid body positions that are known to be problematic. However, research on risk factors for the development of PRMDs is heterogeneous, with many conflicting definitions of PRMD and methods of assessment, making it difficult to understand clear risk factors that may contribute to the development of pain syndromes in musicians.[37] Although some evidence points to relationships between postural factors and PRMDs in musicians, including dysfunction of the lumbopelvic stabilization muscles,[38] forward head posture and protracted shoulders,[39] so far posture has not been strongly implicated as one of the primary risk factors for developing PRMDs in prevalence studies. Available evidence instead points to factors like gender,[40] practice habits and anxiety as having a greater impact on a musicians' risk for developing a PRMD.[41] Most available research tends to diagnose perceived postural defects in musicians without empirically connecting the postures to PRMDs, illustrating instead that according to some clinical definitions of good posture, most, if not all, musicians could be considered to have defective posture.[42] The body of available research on postural interventions as a treatment for PRMDs is small, and so far the results have been inconclusive due to subjective forms of posture measurement.[43] Therefore, although retraining of posture is often recommended as an important part of a treatment plan for PRMDs,[44] there is not yet concrete evidence that interventions aimed at solving postural defects solve or reduce symptoms of PRMDs. More research is urgently needed to further address this issue.

As research proceeds, investigators should consider that establishing the true role of posture in the development of PRMDs will require objective forms of assessment. Conflicting results and theories about the influence of specific postures on musculoskeletal health hinder researchers' ability to interpret whether posture changes following interventions should be considered improvements. Since research has been unable to establish conclusively if certain posture characteristics are clinically problematic, and since posture variables have the potential to vary from day to day within an individual,[45] researchers must contend with the fact that it may be impractical, if not impossible, to apply universal criteria for assessing posture quality across all participants in a study.

Posture quality in piano performance

In the context of piano playing, definitions about what constitutes ideal posture are even more ambiguous. Posture and movement habits vary considerably among professional pianists, making it impossible to define good posture based on technical expertise or movement aesthetics. For instance, Arthur Rubinstein is noted for the erect yet supple nature of his posture, and his parsimonious movement of the torso.[46] His seemingly effortless interpretations, especially of the works of Chopin, are admired as masterful. However, Glenn Gould's peculiar manner of sitting, with a very low seat, hunched back, face nearly touching the keys and raised shoulders, did not seem to interfere with his ability to deliver virtuosic and original performances, even though he struggled with severe musculoskeletal pain during his lifetime.[47] Music educators who teach posture and movement usually draw on a variety of different experiences and movement education systems to formulate diverse opinions about what constitutes good posture, resulting in different preferences among expert educators. These examples demonstrate that there are no defined aesthetic criteria for judging the quality of pianists' posture and movement, making it difficult to judge if changes observed in post-intervention testing should be considered improvements or deteriorations from the perspectives of artistry or technical proficiency. Unless future research is able to specify criteria that can definitively label certain postural characteristics as problematic from the perspective of health or technical expertise, researchers will be unable to confidently interpret the results of intervention studies that objectively measure posture and movement. Until that problem is solved, researchers investigating the impact of somatic training on pianists' posture should look for evidence of change to posture and movement only, without applying criteria for whether the change should be considered better or worse. This will allow researchers to take a more objective first look at the possible influence of somatic training on posture in various areas of the body, instead of ascribing to preconceived expectations based on opinions about posture quality that may not be well-founded in research.

Conclusion: Considerations for measuring posture and movement in the context of the Feldenkrais Method

Choosing appropriate variables for measurement in the context of FM requires researchers to thoughtfully consider the true goals and techniques of the Method. First and foremost, it must be acknowledged that while habitual ways of positioning one's body might be expected to be influenced by the Method to a degree that could be measured with motion-tracking technologies or cameras, FM is not a postural intervention. The Method does not demonstrate specific principles of posture, nor does it require students to practise holding themselves in particular positions. Therefore, researchers studying the impact of FM on posture variables should take care to contextualize posture measurements as one of many possible indicators of change in motor behaviour, and not rely upon them as a means of gauging the success of the Method. Evidence from static positions should be assessed alongside other forms of data, and postural variables should always be interpreted within the context of their relationship to functional movement. It is preferable that studies attempt to include variables related to movement quality, such as range of motion, velocity, acceleration, or jerk, rather than only instantaneous measurements. In the case of research with pianists, variables within movement contexts are particularly important, since we are interested to learn how the motor functioning of pianists is impacted by FM lessons as they interact with their instrument. Instantaneous measurements of posture either before playing, or from selected moments during a performance, can offer only a single glimpse into the functioning of a complex moving system that is influenced not only by biomechanical factors, but also by the musical intentions of the performer.

Feldenkrais adhered to the tenet that posture should not be thought of as a static position but a dynamic process by which the brain solves problems of balance and movement as individuals move through their environment adaptively. He preferred not to use the word 'posture' at all due to its strongly encultured meanings related to ways of holding one's self imposed by societal expectations and physiological manifestations of anxiety.[48] When discussing postural alignment, he preferred to use the word 'acture' to highlight that, in his view, postural alignment is better understood as a dynamic process. 'Acture' describes musculoskeletal organization in the context of movement; the CNS (Central Nervous System) seeks to achieve a state of dynamic equilibrium, self-organizing to maintain balance and satisfy functions of daily life.[49]

He believed that through the exploratory process of learning to sense and feel one's self in movement, people could improve their functionality and ultimately enhance their quality of life.[50] In this view, any state of ideal skeletal alignment or functioning remains purely theoretical, with primacy always placed on individual expressions of movement behaviour, and not the attainment of functional ideals.[51] However, in the twelfth chapter, entitled 'Measuring' Posture (quotations added by himself), of his book Body and Mature Behaviour (1966), he writes the following in regard to the value of quantitative posture measurement:

> I am quite aware that in practice, these methods (of measuring posture) are not more than an indication. It is important, however, that it is possible to obtain some sort of measurement, even though indirect, of what is usually considered very unfathomable. I have little doubt that with the accumulation of extensive data…very useful information would be obtained.[52]

Therefore, by opting for quantitative measurement of changes in body-positioning and movement as part of a research agenda for FM, we are able to fulfil one of Feldenkrais's own wishes. Motion-tracking tools offer the ability to do this, providing a precise means of measuring body-positioning and the possibility of examining movement dynamically through kinematic analyses. Finally, it should be emphasized that our discussion about the value of pursuing objective measures in Feldenkrais research with pianists is not intended to replace qualitative forms of evidence or discount the subjective experiences of practitioners and students. 'These forms of evidence will always remain of primal importance when evaluating the merits and potential of the Method to help people, including musicians. Quantitative measurements of movement and posture can never provide the entire story, but merely constitute an under-represented form of evidence in the current body of literature. Filling this gap could benefit musicians and practitioners of the Method alike by helping increase awareness of and confidence in FM in music education and performance.

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CHAPTER 4: ARTICLE 2

Gaining Insight on the Impact of Feldenkrais Functional Integration in the Context of Piano Playing: Considerations for Measuring Posture and Movement Quality

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CHAPTER 7
GAINING INSIGHT ON THE IMPACT OF FELDENKRAIS FUNCTIONAL INTEGRATION IN THE CONTEXT OF PIANO PLAYING: CONSIDERATIONS FOR MEASURING POSTURE AND MOVEMENT QUALITY

Jillian Beacon, Gilles Comeau and Donald Russell

PART I: THE FELDENKRAIS METHOD AND PIANISTS: A PILOT STUDY OF OBJECTIVE MEASUREMENT OF POSTURE AND MOVEMENT

Playing the piano is one of the most complex feats of motor control that human beings can accomplish.[1] Mastery involves over a decade of dedicated practice to refine and reinforce neurological connections distributed throughout the brain, which must coordinate seamlessly to allow a performer to play with control and expression.[2] The thousands of hours of practice also place formidable demands on the body. Recent research has revealed that playing-related pain is prevalent among professional and pre-professional musicians[3], including pianists.[4] Aspects of body use, such as postural misalignment,[5] excessive muscular tension[6] and biomechanically inefficient playing techniques, are often implicated as risk factors for playing-related pain.[7] Some musicians pursue somatic education as a means of retraining posture and movement to reduce or prevent playing-related pain.

Feldenkrais as holistic mind-body education for pianists

The Feldenkrais Method (FM) is one such form of somatic education. Musicians have used FM's holistic mind-body approach to enhance body awareness and explore new possibilities for coordinated movement. During lessons, students experience functional movement relationships between different parts of the body, helping them become aware of how their entire body coordinates in dexterous action. By exploring movements slowly and mindfully, students may become aware of habits of movement they did not notice before and learn new ways of moving more comfortably. For musicians, this may mean discovering more sustainable ways of playing to reduce or prevent playing-related pain.

Functional Integration in theory and practice

In FM, the style of one-on-one work in which a practitioner gently moves a student's body is known as Functional Integration (Fl). While passively moving the student, the practitioner senses small details in (1) the quality of the student's movement, such as the degree of resistance and patterns of movement transfer between different segments of the body; (2) the body's position, such as asymmetries in orientation and positioning; and (3) the state of arousal in the nervous system, including evidence such as changes in the rate and depth of breathing, and changes in the resting tonus of muscles. Students are usually recumbent during these lessons to allow the postural support muscles (especially the extensors of the back) to relax without having to work against gravity to balance the body upright.[8]

In the short term, these lessons are intended to modulate neuromuscular control of posture globally, impacting the resting tonus of the muscles and students' proprioceptive representation of themselves.[9] Over time, they may lead to neuroplastic adaptations to motor control and an enhanced ability to perceive finer sensorimotor distinctions.[10] These changes may enhance the adaptability of motor behaviour, allowing individuals to move with greater spontaneity and variety. They may also confer other benefits, such as reduced pain or increased ease of movement.

Although each person's experience with FI is unique, it tends to elicit some common sensorial experiences that are reported by many students. People often report feeling taller, or more balanced over their feet in standing, or over their sitting bones in sitting immediately after Fl.[11] Individuals may report feeling that some movements, such as walking or breathing, seem easier,[12] that they have increased range of motion at some joints, or that they have reduced musculoskeletal pain.[13] Some become aware of specific parts of themselves that they could not easily sense or perceive before the lesson.[14] People may also speak of sensory illusions, such as feeling that some parts of the body feel larger or longer than before.[15] These subjective experiences shared by many Feldenkrais students suggest that FM may lead to changes in the mental representation of the body-schema, or self-image, of the person in the central nervous system (CNS) via alterations of their proprioceptive experience. It may also lead to global changes in posture and coordination, stemming from changes in patterns of postural muscle activation that balance and redistribute patterns of resting muscle tonus across the musculoskeletal system. It is therefore reasonable to expect that some evidence of this learning process should be measurable through external measurements of body-positioning and coordination. However, researchers have not yet investigated whether changes in body positioning or coordination patterns can be measured quantitatively.

Objective measurements of pianists before and after Feldenkrais training

As a first step towards addressing the need for objective measurement relating to posture and movement coordination in pianists participating in FM, the authors conducted a pilot project to track and measure pianists' body movements during performance from before and after a single FI lesson. This pilot study had two main objectives: (1) To determine if trends in the vertical alignment of postural points of balance were noted across a group of participants after a single FI lesson, and (2) if specific differences in posture and movement coordination were noted for individual participants. We hypothesized that no group trends in posture change would be observed after a single FI lesson (with Alan Fraser) due to the variability of posture between different individuals, and the natural variability of an individual's posture from day to day.[16] We also hypothesized that changes to specific posture variables might be noted for some individuals, since somatic practitioners and their students often report differences in alignment or movement quality after short-term exposure to the Method.

Investigating Functional Integration with video-based motion-tracking of pianists

We used Dartfish video-based motion-tracking software to track anatomical points of interest on fifteen advanced pianists performing a contrary-motion C-major scale repeated three times, a sight-reading test, and the first section of Beethoven's Für Elise WOO 59 immediately before and after receiving a thirty-minute FI lesson. We hypothesized that integration of sensorimotor experiences of the FI lesson may depend on the cognitive demands of the musical task, and therefore chose playing tests that placed different cognitive demands on the performer. We used Dartfish to track the movement of the pianists because it was simple to set up video cameras non-invasively next to acoustic pianos to permit comfortable and realistic performance conditions for participants. Although Dartfish measurements are limited to two dimensions, this method was appropriate for our study because we wished to measure the vertical alignment of specific anatomical points in the sagittal and coronal planes independently.

Figure 7.1 Placement of anatomical markers for Dartfish tracking (i) canthus (outer corner) of the right eye; (ii) ear tragus; (iii) anterior acromioclavicular joint (shoulder); (iv) C7 spinous process; (v, vi, vii, viii) – T4, T8, T12 and L5 spinous processes.

Posture variables: We fixed anatomical markers on the C7, T4, T8 and T 12 vertebrae of participants, as well as the right eye canthus, right ear tragus, right acromion, right olecranon process and right lateral epicondyle of the humerus (Figure 7.1). We measured the postural variables described in Table 7.1 from videos recorded from the posterior and right sagittal views of the pianists as they performed the playing tests.

Table 7.1 Description of measurement of posture variables for Dartfish tracking

Variable	Description of measurement	Justification for measurement
Head region		
(i) forward head angle (°)	Angle formed between a horizontal line passing through the C7 spinous process and a line connecting the C7 process to the ear tragus	Found to be a good indicator of forward head position.[17] A smaller cervical angle has been associated with increased forward head position and neck pain in computer users.[18]
(ii) head height (cm)	Height of the ear-tragus marker above the origin of the Cartesian coordinate system	A simple way to determine if a person is sitting with more or less spine flexion overall between sessions.
Shoulder region		
(iii) shoulder protraction angle (°)	Angle formed between a line connecting a point on the shoulder and the C7 vertebra and a horizontal line extending forward from the shoulder in the sagittal plane	Gives information about the degree of protraction (forward rounding) in the shoulders.[19] Measured according to the procedure of van Niekerk et al.[20]
(iv) vertical and horizontal shoulder displacement (cm)	Difference between the y-axis value of C7 and the right shoulder	A measurement used by Szeto et al. (2002) to investigate shoulder elevation and shoulder protraction separately.
Spine region		
(v) origin-C7 angle (°)	Angle formed between the x-axis and a line joining C7 to the origin of the coordinate system at the back of the piano bench	Represents the angle of forward inclination of participants as they play.
(vi) T4 angle (°)	Angle formed between the C7, T4 and T8 vertebral markers	Gives an indication of curvature in the upper thoracic region of the spine.[21]
(vii) T8 angle (°)	Angle formed between the T4, T8 and T12 vertebral markers	Gives an indication of curvature in the lower thoracic region of the spine.[22]
(viii) T12 angle (°)	Angle formed between the T8, T12 and L5 vertebral markers	Gives an indication of the curvature in the lower thoracic/upper lumbar regions of the spine.[23]
(ix) height of vertebral markers (cm)	Height of spine markers (C7, T4, T8, T12, L5) above the origin of the Cartesian coordinate system	Used to measure changes in vertical positioning of specific vertebrae in the spine.

Table 7.2 Cross-participant average measurements of angular posture variables from before and after FI intervention in three playing conditions (°)

Variable	Playing condition	Pre-test	Post-test	Difference
Forward head angle (°)	Scale	31.3	31.7	0.4
	Für Elise	29.9	30.6	0.7
	Sight-reading	32.2	32.4	0.2
Shoulder protraction angle (°)	Scale	43.5	43.6	0.1
	Für Elise	49.6	49.4	–0.2
	Sight-reading	38.8	33.7	–5.1
T4 angle (°)	Scale	150.7	151.2	0.5
	Für Elise	150.8	151.2	0.4
	Sight-reading	150.8	150.9	0.1
T8 angle (°)	Scale	166.1	166.2	0.1
	Für Elise	166.0	166.4	0.4
	Sight-reading	166.0	166.2	0.2
T12 angle (°)	Scale	182.2	181.9	–0.3
	Für Elise	181.7	180.9	–0.8
	Sight-reading	182.7	180.7	–2.0

Notes. An increase in forward head angle means the head has moved backward into a more erect position.
A decrease in shoulder protraction angle means the shoulders are moving forward, becoming more rounded.

Comparing group averages of posture variables: Results revealed that posture variables and movement patterns tended to remain consistent for most participants between the first and second sessions. No group trends in posture change were noted from pre- to post-test for any posture variables measured in the head, shoulders and spine regions. The group averages for spine angles were particularly stable between sessions and across playing conditions (see Table 7.2).

Changes to posture and movement characteristics of individual participants

We were also interested in finding out if significant changes in posture variables or movement patterns could be noted for individual participants. To answer this question, we examined time plots of posture variables of individual participants throughout the duration of their first and second sessions performing each playing test. time plots from both the pre- and post-test recordings frequently displayed very similar movement patterns for a given participant' often containing even small details of torso movement at the exact same musical points in the phrases. The stability of the movement patterns can be clearly observed in Figure 7.2, which displays the pre- and post-test time plots of participant EFI's body flexion angle during their performance of *Für Elise*.

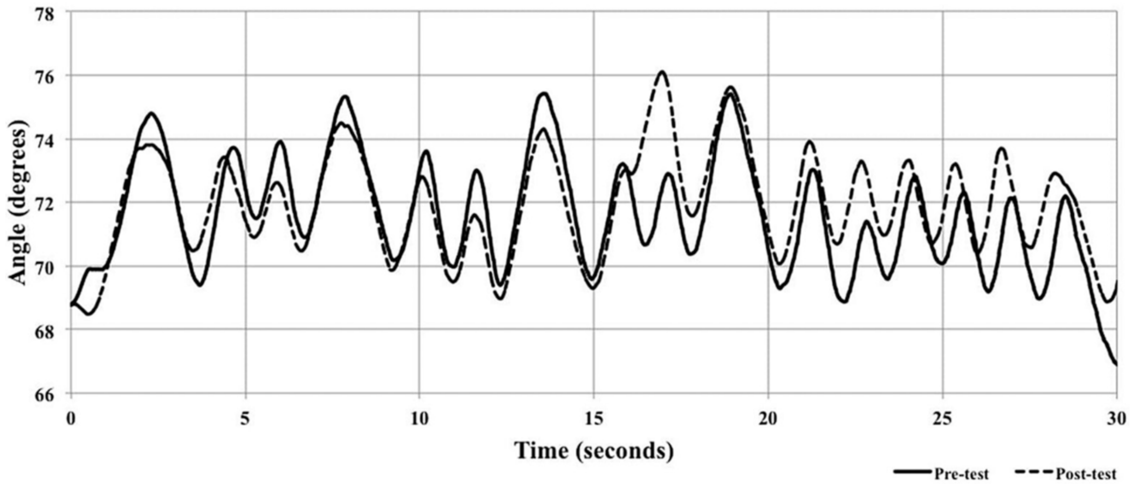

Figure 7.2 **Pre- and post-test time plots of the angle between a line connecting the C7 marker and the point of origin on the bench, and the *x*-axis for participant EF1.**

However, time-plot analysis also revealed that some individuals displayed strikingly different movement patterns in pre- and post-test recording sessions. For example, Figure 7.3 illustrates that in the pre-test, participant KP2 kept her head almost perfectly still. Her pre-test head movement appears jerky, with a limited range of only about 3 degrees. In the post-test, the participant's head appears to have moved in a smoother, wavelike pattern compared to the pre-test, and the range of motion increased to about 10 degrees. It is interesting to note that this difference in pre- and post-test head movement patterns was noticeable in both the scale and Für Elise performances, but not the sight-reading condition, suggesting the movements of the head may have been restricted when the participant was required to read unfamiliar music.

Figure 7.4 displays a second example of differences in movement quality, illustrating an increased range and apparent smoothness of movement of the head and torso of participant AL1 in the post-test compared to the pre-test performance of contrary-motion C-major scales. This example is interesting because it clearly depicts a consistent movement pattern in the torso throughout each of the three repetitions of the contrary-motion scale. The changes in movement quality appear to be integrated throughout the head and spine, since the differences appear for angles of head elevation (A), hip flexion (B) and lumbar curvature (C). The post-test movements had a greater range of motion and showed fewer instances of abrupt changes in positioning. However, it is noteworthy that these changes only appeared in the scale-playing condition for this participant, and not the other tests.

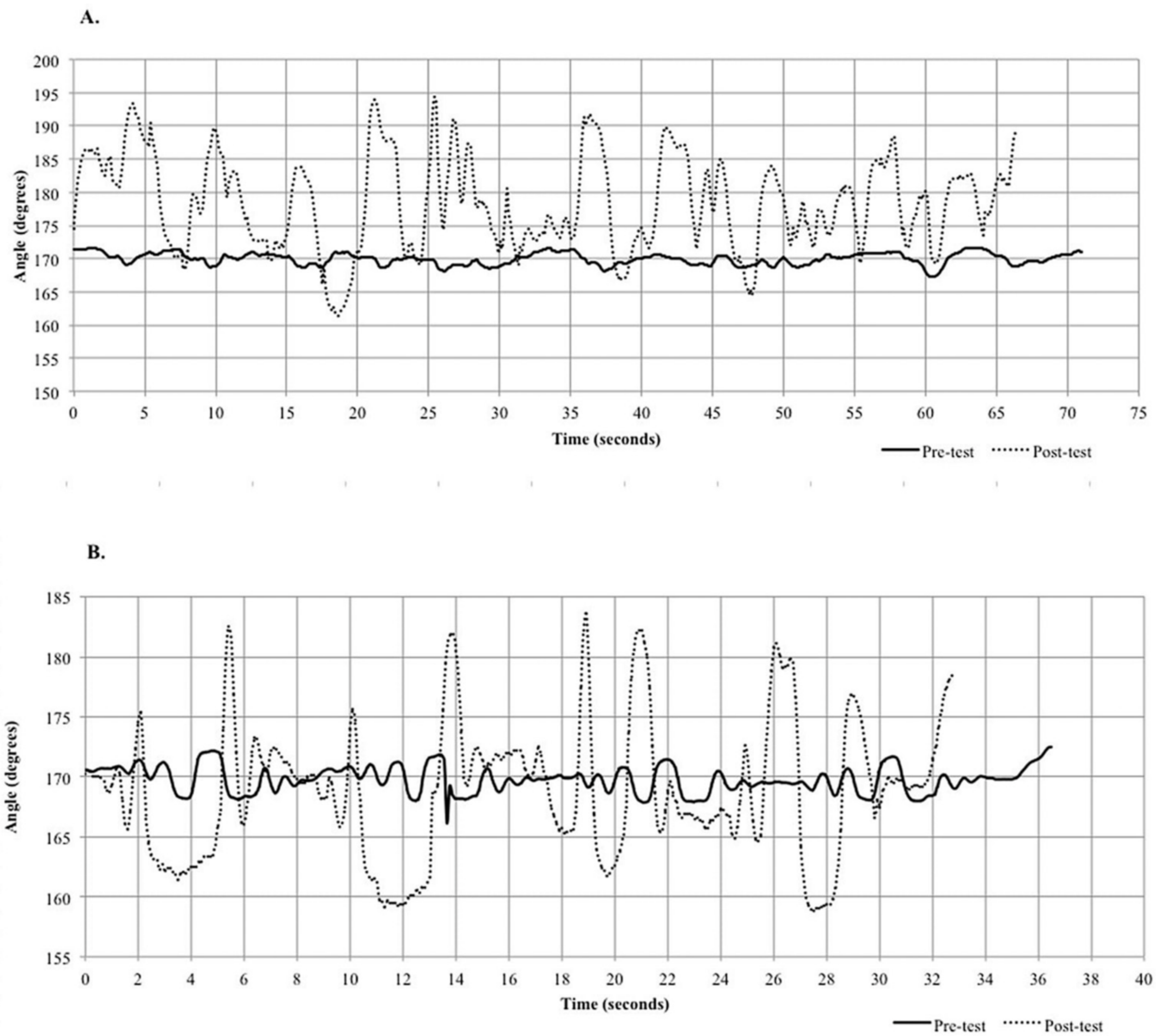

Figure 7.3 Pre- and post-test time plots of the angle formed between the horizontal plane and a line connecting the C7 vertebral marker and the eye-canthus marker for participant KP2 during (A) *Für Elise* and (B) scale performances.

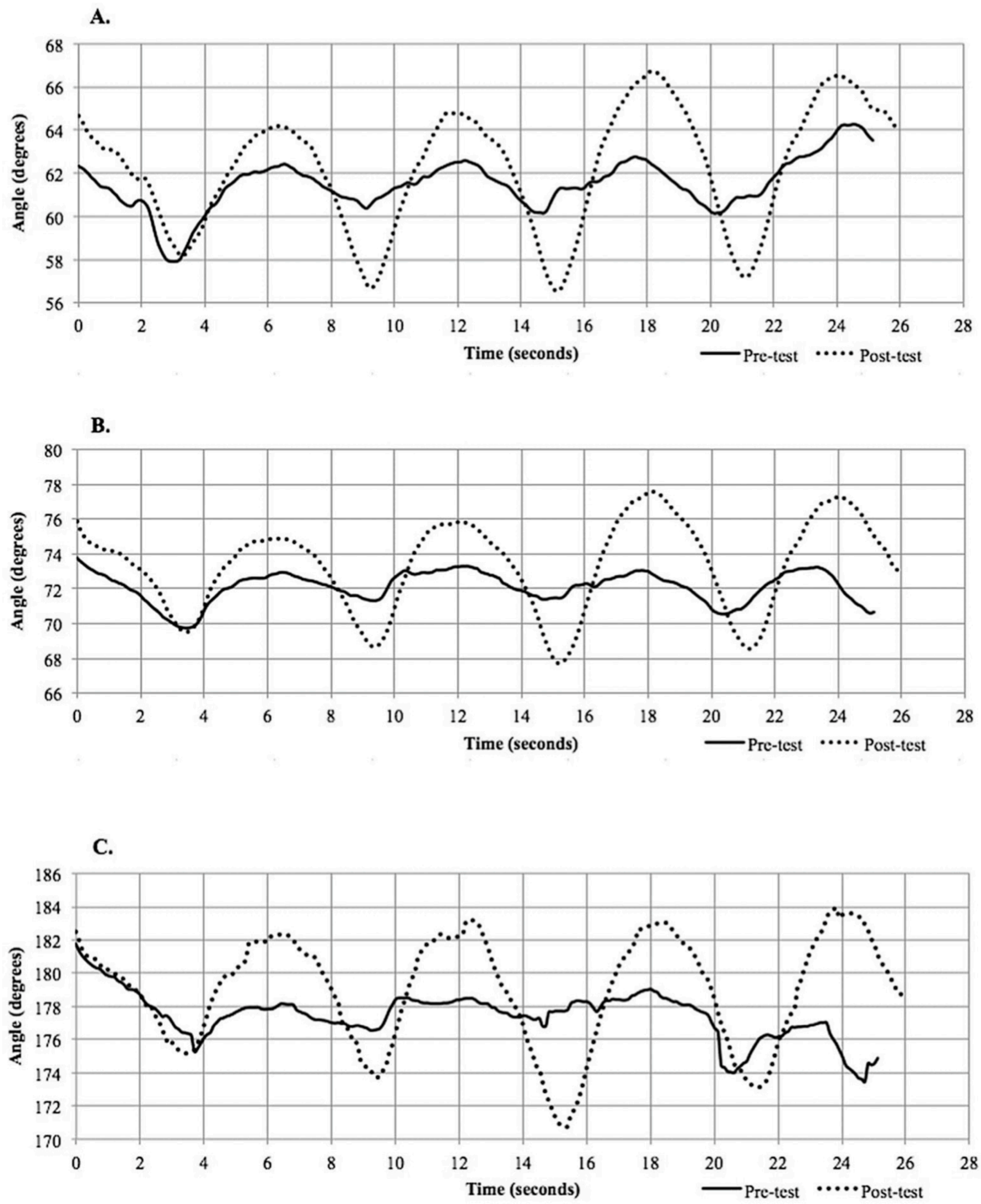

Figure 7.4 Pre- and post-test time plots of (A) eye-canthus, C7, horizontal angle, (B) C7 marker, horizontal angle, and (C) T12, L5, vertical angle for participant AL1's performance of scales.

PART II: DISCUSSION AND RECOMMENDATIONS FOR FUTURE RESEARCH

The results from this pilot study are intriguing and offer an opportunity to discuss many issues regarding the strengths and limitations of measuring posture as the dependent variable in repeated measures studies with FM. In the following sections we raise five important points stemming from our pilot investigation that future researchers may find helpful when constructing methodologies for quantitatively examining patterns of human movement in the context of music performance.

Recommendations for study design: Researching individuals instead of groups

The most interesting results from our pilot study came from examining data on an individual basis rather than looking for group trends. For instance, participant API's movement became more integrated throughout the torso during scale performances. We also observed larger, more graceful head movements in participant KP2's post-test recording compared with her pre-test recordings, which show that she held her head almost perfectly still before the Fl. Although more than two measurement sessions would be required to determine if the changes observed reflect natural variability in movement or changes induced by El, these examples are intriguing and warrant further investigation.

The fact that the two participants did not respond in the same way should not diminish the significance of the observations; it is expected that individuals will respond differently to FI since each participant has unique movement habits, and personal histories of training, pain and injuries. Researchers struggle to identify variables that could be meaningfully assessed across a large sample group in a large randomized controlled trial (RCT). Future research on FM may be best served by capitalizing on detailed, single-subject designs employing objective measurements of movement behaviour of individuals over longer periods of time. Although RCTs are still considered to be the gold standard of scientific evidence,[24] many human movement researchers are beginning to recognize that the dynamic, evolving and adapting nature of the human motor system requires detailed examination of unique individuals in single-subject methodological designs.[25] This style of investigation is certainly well suited to FM, achieving a necessary balance between the individualized attention afforded in case studies and the objectivity of the scientific method. This is especially true for pianists, who as a group vary in level of expertise, type of dysfunction or discomfort experienced, and playing history, making it difficult to achieve participant homogeneity in large-scale research projects.

Recommendations for variable selection: Measuring movement

Our pilot project raises questions about the limitations inherent in studying posture as a static position. Most studies that quantitatively measure posture use static standing or seated positions.[26] Up until recently, researchers have tended to prioritize methodologies which attempt to define ideal or average measurements for resting angles in spine curvature,[27] shoulder position,[28] or head and neck positions,[29] but without standardized measurement protocols it is difficult to compare results across different studies. Methodologies examining static posture variables could help assess some physiological outcomes of FI, but they are ultimately unable to address changes in movement quality, timing, orientation and coordination, which are central concerns of FM.[30] Moshe Feldenkrais believed in a principle of dynamic equilibrium, by which posture is thought of not as a position but rather as a process through which the CNS finds functional ways to move gracefully and find balance using sensory feedback.[31]

Researchers could address this perspective on posture by exploring analytical approaches that report on the quality of movement, such as smoothness and range of motion, rather than static joint positions. Researchers could also apply biomechanical strategies for studying coordination in intersegmental relationships to describe how changes in one area of the body impact or evolve with changes in another area dynamically during movement. One method to examine how changes in one joint angle relate to changes in another is to use parametric phase plots to describe the continuous relative phase between two moving oscillators.[32] Some motor control researchers have used this type of analysis to examine movement relationships between the head and thorax in walking,[33] and studies with pianists could conceivably use this method to examine how movements in joints of the arms are related to movements in the pelvis or thorax for repetitive playing tasks. However, this type of analysis is best suited to movements that repeat and can be described periodically. Since many pianistic movements are not typically periodic and may vary considerably depending on the technical and expressive demands of the music, this type of analysis may only be practical in a limited number of music performance contexts.

Principal component analysis (PCA) is another possible method for examining features of coordination in human motion-tracking data. PCA is a form of analysis used to reduce large kinematic data sets into components identifying specific movement relationships that account for portions of the variability in the entire moving system. PCA uses algorithms to identify mutually orthogonal directions of maximal variance in a data set to compile new data sets, or principal components (PCs), that are ordered according to the amount of variance they explain. Each PC is an independent linear transformation of the original data set, and in kinematic analysis these transformations are often interpreted to represent meaningful movement relationships within the entire system. The benefit of PCA is that it can reveal movement relationships between many different areas of the body at the same time, and researchers do not have to limit analysis to only one or two joints.[34]

This method has already been used in some applications with musicians. For example, researchers used PCA to extract movement features from the hands of four pianists with differing levels of expertise. [35] The researchers tracked twenty-six anatomical markers on the pianists' hands as they played six different piano pieces. Analysis revealed that often eight or more PCs were required to describe the movements of the more experienced pianists while fewer PCs were required for pianists with fewer years of experience. This suggests that the experts more flexibly exploit the degrees of freedom available in the hand and use a greater diversity of hand movements compared to amateurs. Although this study only examined four pianists, the ability of PCA to identify more degrees of freedom in the hand movements of expert compared to amateur pianists suggests future research is warranted. Researchers could investigate if PCA is suitable for comparing motor behaviour between musician populations expected to display differences in dexterity, such as injured and uninjured musicians, or musicians with and without somatic training experience. Although PCA offers a powerful way to extract features from complex movement data, the method comes with limitations. The movement relationships uncovered using PCA may be difficult to interpret biomechanically since they do not necessarily represent real movements,[36] and there is a potential for loss of detail in explaining the variance if the variance threshold is set too low in the algorithm.[37]

The results of the analysis can change drastically depending on the user-determined settings, such as the percentage of total variance the algorithm will explain in the data set or processes of data normalization. PCA is also more suitable for identifying differences between groups of movers already suspected of exhibiting differences in motor behaviour. It is not clear if PCA analysis is a suitable means for tracking subtle changes to coordination that may be brought about by somatic training across pre- and post-test trials. Although researchers have already used PCA to create movement profiles to describe individual pianists' movements,[38] researchers have not yet established if these profiles tend to remain consistent for repeated performances of the same piece. For these reasons, more testing will be required to determine its suitability as a measurement technique in repeated measures studies of FM with pianists.

Recommendations for baseline measurements: Assessing variability in baseline posture

Future studies on FM with musicians should incorporate comprehensive baseline testing to better understand the range of normal measurement values for each individual participant. Since our study did not conduct baseline testing over many days, we were unable to distinguish potential changes brought about by the intervention from natural fluctuations in motor behaviour. Human postural coordination varies day to day because it is mediated by complex and highly adaptable motor control strategies in the CNS that can easily be influenced by factors intrinsic to the participant or their environment and potentially lead to variability in baseline measurements.[39] Postural control can be impacted by cognitive loading[40] and attentional demands of competing tasks,[41] with the impact becoming more significant as age increases.[42]

Postural sway and the natural variability of head and spine positions present serious obstacles for researchers attempting to track changes to posture in repeated measures studies.[43] For instance, Dunk and colleagues found poor repeatability of posture measurement of thoracic, cervical and lumbar curves when measured across three sessions, with the first session conducted in the morning, and the second and third sessions taken a week later in the morning and afternoon.[44] Pownall and colleagues found that the posture variables of eleven healthy men remained stable during measurements taken over the course of one week, but posture variables in the sagittal plane, including spine variables, were more inconsistent compared to variables measured in the posterior or anterior view.[45] Whichever postural variables researchers choose to measure, it is important that researchers take the time to learn how their variables naturally fluctuate over a period of several days or weeks, and carefully control testing conditions to reduce the influence of environmental factors that may influence postural coordination.

Choosing musical tests: Task-dependent posture

Since research demonstrates that cognitive loading impacts neurological posture control strategies,[46] we hypothesized that the type of playing task performed by a pianist could significantly influence their postural characteristics during playing. The results of our pilot study lend preliminary support for this hypothesis. For instance, we noted that the relative size of forward head angle stayed consistent from pre- to post-test for a given participant performing a given playing task. This suggests that an individual adopts a different average position of the head depending on the task, and that these individual tendencies seem to remain consistent despite a single FI lesson. We also observed that each pianist displayed a greater average angle of elbow abduction on the right side compared to the left side from the anterior view in both the pre- and the post-tests (Figure 7.5). This is interesting because C-major contrary-motion scales involve identical biomechanical demands on the right and left side of the body; the movements are perfectly mirrored, the same fingers play at the same time in both hands, and the distance the individual's arm must travel on the keyboard is also the same. Since most individuals sat at the keyboard with middle-C very near to the centre of their bodies, one might expect biomechanical symmetry in the movements of the right and left arm to match the symmetry of the task demands. However, it appears that all participants have learned a right-side dominant strategy to perform the contrary-motion scale, regardless of handedness (there were three left-handed individuals in the study). This gives a clear example of how it is possible for the brain to use different movement strategies for the right and left side of the body even when they are completing the same task. In this case, this type of asymmetrical movement strategy seems to be common for the performance of this particular scale and this tendency did not seem to be impacted by the FI lesson.

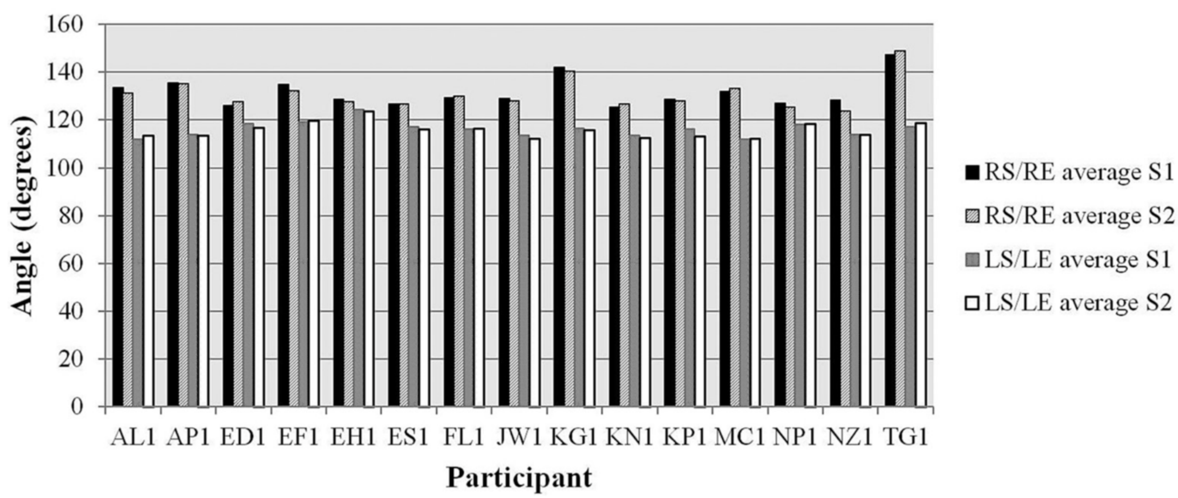

Figure 7.5 Average angle of abduction between a line connecting the elbow and shoulder, and a vertical line descending from the shoulder on the right and left sides in performances of contrary-motion scales before and after an FI intervention. RS/RE stands for 'angle of right shoulder to right elbow'. S1 is the pre-test and S2 is the post test.

Our observations of task-dependent posture concur with other researchers' observations that musicians' movement characteristics differ between sight-reading and repertoire playing conditions.[47] Therefore, researchers investigating posture of pianists must consider that the varying cognitive demands of different types of performing tasks could significantly impact posture control strategies during performance, and should control for the type of activity the pianist measures tests. Future research will be required to better understand task dependency on posture when constructing methodologies to investigate somatic training outcomes with pianists.

Drawing conclusions from posture research: What is an improvement?

Even if studies successfully measure posture variables, researchers have yet to reach a consensus about how to interpret the meaning of those measurements in terms of improvements to health or performance. Researchers struggle to define how extreme a postural measurement must be to count as pathological, and many cases have been unable to find clear correlations between certain posture characteristics and musculoskeletal pain. For instance, some evidence indicates that rounded shoulders are associated with higher incidences of musculoskeletal pain.[48] However, since the repeatability of shoulder measurement has been shown to be unreliable between different raters and across multiple measurements from the same rater for some measurement protocols, it is difficult to draw conclusions from available research.[49] Correlations of specific spine positions with musculoskeletal pain are particularly ambiguous.[50] Although research shows that variations in spinal curvature can alter how trunk muscles are activated to support the body,[51] the details about how certain characteristics of spinal curvature influence musculoskeletal health are not well understood, and diverging theories create confusion about the definition of healthy spine posture.[52] For instance, some researchers still disagree about whether a kyphosis or lordosis curvature in the lumbar spine is healthier for seated posture,[53] and how proper posture should be taught for the prevention of lower back pain.[54] Evidence also shows that structural abnormalities in cervical spine curvature are not correlated with higher incidences of neck pain, even though they are often considered to be the cause of pain in clinical settings.[55] The case against forward head position is much clearer, with more substantial evidence that smaller angles Of forward head position (occurring when the head is held further away from the body anteriorly) correlate with higher incidences of musculoskeletal pain in the neck and shoulders.[56] However, some researchers have cautioned against drawing conclusions too quickly even in this case, since classifications of forward head position have varied across different studies.[57] These confusions illustrate that although superficially it may seem like a simple task to create criteria for judging posture quality and to choose posture variables for measurement in research, the many divergent opinions presented in the literature pose significant challenges to researchers. Although many modes of treatment for musculoskeletal disorders operate based on their own theoretical principles of correct postural alignment, currently there is no scientifically defensible criterion for judging whether posture could be said to have improved or deteriorated in repeated measures studies on somatic training.

Conclusion: New directions in research on the Feldenkrais Method with musicians

Our pilot study offers preliminary insight into the expected impact of FI lessons on body positioning and movement in pianists. This project yielded five main insights that could help guide researchers in future studies on FM with musicians: (1) Research on FM with musicians may benefit from single-subject designs that use rigorous empirical methods to study changes in motor behaviour in individuals; (2) Research on how FM influences movement quality and coordination may yield more poignant results compared to measuring static posture variables, or averaging positions from motion-tracking data; (3) Future studies should include comprehensive baseline measurements to better understand the natural variability of the dependent posture and movement variables; (4) The posture and movement exhibited by a musician may be significantly influenced by the type of playing task they perform; and (5) Researchers should acknowledge that it is difficult to interpret the meaning of posture measurements within the literature relating posture to health and function.

Since the current scope of research in this field is limited, researchers could consider applying some of these insights in investigations about longer-term impact of somatic training interventions, including FM. We have a paucity of data on the transition that a piano performer might experience as they learn new motor behaviour through FM, and the time scale over which these changes are observable. This should entice researchers to work to find ways to answer many important questions regarding the process and applications of somatic learning, including: (1) Which factors influence the development of biomechanical strategies such that some pianists are pain-free, while others encounter limits to their motor capacity or develop playing-related pain? (2) How do biomechanical strategies differ between injured and non-injured pianists and how can Feldenkrais lessons help? (3) How do biomechanical strategies evolve over somatic learning periods of different time scales? (4) Do biomechanical strategies keep evolving once somatic lessons are over? (5) Are specific biomechanical factors influenced differently by different somatic approaches?

A motivation behind the pursuit of such studies is the urgent need for new research that objectively examines somatic training outcomes, since most evidence suggesting that somatic training can lead to improvements in playing-related pain or musical expression comes from subjective sources. FM and other somatic approaches have helped many musicians feel more comfortable when performing, and increasing awareness about these methods may help to improve the quality of life of many performers, especially students who experience tremendous workloads and high degrees of physical and emotional stress during their study.[58] However, Universities and conservatories will need credible evidence from research about the benefits Of these methods to justify the cost of incorporating them into programming. Since somatic training lessons are not often covered by medical insurance plans, they are not always affordable for the musicians who may benefit from them. Improved research could pave the way for the eventual coverage of somatic training by insurance plans or may at least help students become informed about the potential benefits of somatic training, should they choose to invest their time and money into learning them. Finally, improving research methodologies could help FM practitioners better understand the specific mechanisms responsible for musicians' positive experiences with FM. This could lead to better adaptation of teaching strategies to the unique needs of performing musicians and improve the quality of somatic training in the context of music education.

Notes

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CHAPTER 5: ARTICLE 3

Evaluating Standard PCA as a Tool for Measuring Coordination Characteristics in Pianists

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Abstract

Pianists frequently seek out movement retraining specialists to help them learn new approaches to posture and movement that may reduce musculoskeletal discomfort related to playing their instrument and improve the quality of their performances. It is postulated that movement retraining leads to improvements in music performance quality and discomfort via the mechanism of altering the performer's habitual movement characteristics. Therefore, successful movement retraining should elicit measurable changes in pianists' coordination characteristics during musical performance. Quantitatively measuring and describing such changes to coordination characteristics would provide objective evidence that movement retraining directed at musicians is effective in helping them learn new approaches to posture and movement. However, recording pianists' movement using optical based motion tracking creates large, multivariable datasets representing movements from many different areas of the body simultaneously. Understanding the effects of movement retraining on the coordination characteristics of joints distributed across pianists' bodies requires analytical approaches capable of revealing patterns across many different anatomical variables during the performance of complex, bi-manual musical patterns.

Principal component analysis (PCA) could be a useful tool for detecting variation related to specific coordination characteristics of pianists that may be hidden in the motion capture data. First developed in 1901 by Karl Pearson (Pearson, 1901) before being further developed by others including Harold Hotelling (1933) and Ian Jolliffe (1972, 1973, 2022), PCA has evolved to become an important tool for detecting and defining independent patterns of variation hidden in complex, multi-variable data systems, such as financial indices (Nobre & Neves, 2019),

weather measurements (Azfar et al., 2015), and virus genomes (Wang & Jiang, 2021). PCA has been successfully applied to better understand variation in movements such as walking (Verrel et al., 2009; Troje, 2002) and jumping (Cushion et al., 2019) and has even been applied in the study of musical performances (see review below). However, it is unclear from current research if standard PCA on its own is capable of detecting variation related to participant-specific coordination characteristics of pianists that can be tracked and measured over time to reveal subtle changes in body organization in response to movement retraining interventions. In this paper, we use the term 'standard PCA' to refer to the practice of conducting a PCA on a data matrix comprising columns corresponding to each of the x, y, and z motion capture trajectories from each anatomical marker, simultaneously. The data is not subjected to pre-processing steps outside of standard practices such as mean centering, normalizing to a standard deviation of one, or filtering for noise frequencies.

This exploratory study seeks to take the first step toward a better understanding of standard PCA's suitability for measuring subtle changes in pianists' coordination characteristics by applying it to motion capture data of six advanced pianists performing tasks of varying levels of complexity, and comparing the results from three measurement sessions, each a week apart. Results demonstrate that standard PCA applied to the entire set of anatomical markers simultaneously is insufficient to draw distinction between different pianists or between different measurement sessions. We recommend that the next required step in developing piano specific PCA procedures for measuring the impact of somatic training on coordination characteristics requires the development of a new framework that can better categorize different types of variation contributing to the overall variation in motion capture data obtained during musical performances. Such a framework will help guide researchers in the development of novel procedures for refining PCA to target specific sources of variation related to unique coordination characteristics of individuals that can be tracked and measured over repeated trials of musical tasks.

Keywords: Principal Component Analysis, PCA, coordination characteristics, complex movement, piano performance, movement variation

Evaluating Standard PCA as a Tool for Measuring Coordination Characteristics in Pianists

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5.1 Introduction

Pianists frequently seek out movement retraining specialists to help them learn new approaches to posture and movement that may reduce musculoskeletal discomfort related to playing their instrument and improve the quality of their performances. Pianists may consult with professionals from diverse backgrounds in search of specialized help that addresses their specific needs, including physiotherapy, occupational therapy, and sports medicine, or from complementary somatic approaches, such as The Feldenkrais Method® or The Alexander Technique™. Theoretically, practitioners of these modalities can help pianists identify habits of posture or movement that may be limiting their musical capacity or causing discomfort and teach them to adopt new ways of moving that enhance fluency and agility, aiding not only in improvements to their playing, but also reducing musculoskeletal strain and symptoms of playing-related pain. It is postulated that movement retraining leads to improvements in piano playing via the mechanism of altering habitual movement characteristics. Therefore, successful movement retraining should elicit measurable changes in pianists' movement characteristics during musical performance over time. Quantitatively measuring and describing such changes to movement characteristics would provide objective evidence that movement retraining directed at pianists is effective in helping them learn new approaches to posture and movement at the piano.

Unfortunately, there is very little objective research examining if movement re-training interventions are successful in helping pianists adopt new approaches to posture and movement at their instrument. Research suggests that each pianist's approach to playing is habituated and personal (Bernays & Traube, 2014). The cognitive and motor demands of bi-manual piano performance are sufficiently great that expert pianists rely on highly automatized motor patterns to execute the complex movements performance requires (Van der Steen et al., 2014). It is hypothesized that after years of intensive piano training, these highly automatized patterns are difficult to replace without at least temporarily reducing performance quality, since at first the new, less familiar ways of moving suggested by therapists place greater cognitive demand on the performer's attention. It may be that pianists require a slower and more methodical approach to movement re-training that helps the nervous system gradually learn new movements, giving time for new motor pathways to develop that are sufficiently robust to supplant the older, more automatic pathways. Currently, research has not provided objective evidence that movement retraining succeeds in helping pianists replace existing movement habits with alternative ways of moving, nor that any changes to movement persist after the intervention has ended. Objective research is required to better understand how pianists' highly automated movement patterns respond to movement retraining interventions over time and could help practitioners learn how to better adapt their practice for work with pianists.

However, tracking and measuring subtle changes in pianists' movement characteristics present challenges to researchers. In clinical situations, experienced therapists and somatic practitioners rely on visual observations of posture and movement to gain insight into how the training is progressing (Fortin et al., 2011). Experts in movement therapies become skilled at noticing small details in their students' movement characteristics that may not be apparent to the untrained eye (Whatman et al., 2013). However, although experts' visual assessments are indispensable in clinical settings, they are insufficient for objectively measuring how movement characteristics change over time in quantitative research studies because of the subjective and qualitative nature of visual assessment (Fedorak et al., 2003; O'Leary et al., 2015). Objective research on the impact of movement retraining interventions requires quantitative means of measuring pianists' movement characteristics that can be tracked over time. Such measures would allow researchers to quantitatively describe individual pianists' movement characteristics, measure the stability of those characteristics over time, and determine how they respond to movement retraining interventions.

5.1.1 Measuring Coordination Characteristics in Piano Playing

Quantitative study of pianists' movements can be achieved using optoelectrical motion capture technology to track the position of reflective markers positioned on anatomical landmarks distributed over body. Although motion capture technology makes it possible to accurately track and measure pianists' body positions, researchers are faced with the challenge of finding data analysis techniques for understanding how the movement of different markers are functionally related. Broadly speaking, researchers studying how movements in different parts of the body are related are seeking to understand body coordination. Coordination, as it relates to relationships between moving parts in a human body, has been defined many ways in research depending on the purposes and methods of individual studies (Forner-Cordero et al., 2005). For the purposes of this research, the term *coordination* relates to how measures quantifying aspects of movements from across different parts of the body, such as position, velocity, acceleration, or timing, are organized to support functional movement, such as standing, reaching, or playing a musical instrument. For instance, one might be interested in how movements of the pelvis, spine, and head are organized in time and space to allow a person to turn and look to the right while standing (Hollands et al., 2004). In this paper, the term coordination will always refer to characteristics about how movements of different parts of the body are organized. The word *coordinated* will not be used as a qualifier to describe the degree of a person's dexterity or agility.

The factors influencing how different parts of the body are coordinated in functional movements are diverse. *Coordination characteristics* arise from a combination of musculoskeletal constraints, neurological features of the sensorimotor system relaying information between the muscles and the central nervous system, and task characteristics. Coordinated human movements are inherently variable and are expected to fluctuate slightly over repetitions of a given movement (Turvey et al., 1982, p. 246-251). Coordination characteristics can also be influenced by learning/practice effects (Wu & Latash, 2014), diseases related to motor dysfunction (Benedict et al., 2011; Morris et al., 2001), the presence of injury or pain (Merkle et al., 2020), and aging (Seidler et al., 2010). Motion tracking can only measure the output of the different intrinsic and extrinsic factors contributing to coordinated human movement. Therefore, 'coordination' itself cannot be directly measured. Instead, researchers must collect high-quality data describing body position over the course of a movement and find analysis methods that can help identify underlying relationships describing how different parts of the moving system are organized. Repeated measures studies examining how pianists' coordination characteristics respond to movement retraining require analysis methods that provide evidence of coordination characteristics that can be tracked over time, allowing researchers to distinguish natural fluctuations in the coordination characteristics from any changes that may be related to the intervention.

Existing research seeking to quantify musicians' coordination characteristics generally focuses on measuring discrete movements by isolating a specific sub-movement occurring within a larger movement context and choosing the most important anatomical locations to measure. For example, Furuya and colleagues studied coordination characteristics of professional and amateur pianists' hand and arm movements during the performance of tremolos (*i.e.*, rapid oscillation between two notes using one hand) (Furuya et al., 2011). By isolating a few joint positions on the hands and arms and limiting the study to a specific, repetitive key striking task occurring at one location on the keyboard, the researchers successfully quantified differences in the velocity of some hand movements, such as thumb flexion, and elbow pronation and supination, in professionals compared to amateurs. The team discovered that professional pianists have smaller average extension angles at the metacarpophalangeal joint of the index and middle fingers compared to amateurs for tremolos. Similarly, Furuya and Kinoshita (2007) compared the relationships in the timing of shoulder, arm, wrist, and finger joints during the performance of unimanual harmonic octave keystrokes at different loudness levels in seven novice and seven expert piano players. They found kinematic evidence in joint angles and timing of movements that indicated a clear proximal to distal organization in experts that was not present in novices.

Although studies like these provide detailed insight into the characteristics of specific movements relating to isolated areas of the body during discrete, unimanual piano movements, similar methodologies would be unsuitable for studies seeking to understand coordination across the body during the performance of a complete, bimanual piano piece. This is because a performer employs a variety of small-magnitude movements distributed throughout the body when playing the piano. During a typical piano performance, the pianist remains seated, with their arms flexed at the humeroulnar joint and palms pronated. The head may turn right and left to assist with visually locating notes on the keyboard. If the pianist is playing from sheet music they will almost exclusively gaze forward at the musical score, relying on peripheral vision and occasional glances at their hands to target the keys. Their glenohumeral joints will abduct, adduct, and flex slightly to move to different places on the keyboard. The spine will flex, extend, and rotate to allow the pianist to reach further to the left and right extremes on the keyboard. Pianists may also change the hip flexion angle to the adjust the distance of their arms from the keyboard and to employ trunk and pelvis musculature to aid in tone production. The greatest number of movements occur in the fingers and wrists as the pianist repeatedly flexes and extends the fingers to play piano keys. During key striking movements, the metacarpophalangeal joints flex and extend, the thumb adducts, abducts, and opposes, and the wrist flexes, extends, abducts, and adducts. There are even small movements at the radio-ulnar joints allowing the forearms to slightly supinate away from a fully pronated position. Although all these movements are critical to the performer's agility and the quality of their performance, the size of any individual movement is very small. Most joints involved in piano playing move through a very narrow portion of their total possible range of motion. Any of these small movements may be influenced by movement-retraining interventions due to the reorganization of the interconnected parts of the musculoskeletal system. Choosing one location to best represent a pianists' coordination *a priori* is almost impossible, since each pianist will present with different existing coordination characteristics that may respond differently to the training. Changes to coordination characteristics may arise from small adjustments to a variety of sub-movements or different locations in the body, and the size of change in any one anatomical variable is likely to be very small and difficult to distinguish from expected natural variation. The importance of movement occurring at any individual joint is best understood in terms of how it contributes to a larger pattern of coordination across the body.

As a result of the distribution of small-magnitude movements across the body, researchers studying the effect of movement re-training interventions on pianists' coordination characteristics require novel approaches to motion analysis that do not rely on isolating one or two posture variables to be averaged over the course of a performance. Instead, researchers require an analytical approach capable of quantifying moving relationships between different parts of the body that is sensitive enough to track changes to subtle changes to coordination characteristics over time.

5.1.2 Principal Component Analysis

A method called *Principal Component Analysis* (PCA) could provide researchers with a way of better understanding pianists coordination characteristics by providing a means of studying variation in the motion capture measurements representing body movements. Mathematical calculations of variation quantify how changes in the measurements of one variable relate to changes in the measurements of another variable. For example, in a simple two-variable system, it is possible that as the measurement value of one variable increases, the other decreases. This kind of relationship is called negative correlation. Alternatively, the two variables may increase or decrease together, resulting in a positive correlation. Two variables may also be uncorrelated, meaning that the variation in one is unrelated to variation in the other. Although more difficult to visualize, using PCA it is possible to mathematically account for variation characteristics in more complex systems with many more than two variables, as occurs in motion capture data sets with multiple anatomical markers, each with their own *x, y,* and *z* trajectories representing independent variables in a dataset.

PCA describes independent variation characteristics contributing to the overall variation in a complex system of variables. PCA algorithms identify ranked vectors that can be used to identify dominant variation characteristics in the data set. It uses linear algebra to find the vectors of maximal variance, which can be thought of as "directions" or "axes" within the data set. The vector of maximal variance is referred to as the first "principal component" (PC), which represents the axis in the data set along which occurs the greatest proportion of variation overall in the data set (for those familiar with linear algebra, the first PC is the linear combination of the data that results in maximum variance). The PCA algorithm repeats the process of finding subsequent principal components for all dimensions in the data set, taking the vectors of maximal variance perpendicular to the preceding component until there are as many PCs as there are variables in the data set. In principle, this process is similar to drawing successive, independent "lines of best fit" through the data set, each representing an increasingly smaller amount of the overall variance in the data set. However, these lines of best fit are not represented in three-dimensional space, but in a dimension equivalent to the number of variables included in the PCA. The result is a list of PCs ordered according how much variance each one explains, with PC one explaining the greatest amount of variance, PC two explaining the second greatest amount of variance, continuing until the last component which has a rank equivalent to the dimension (number of columns) in the matrix. Each PC represents a vector, that when multiplied by its corresponding set of coefficients, will reconstruct the original data along that vector. Many papers refer to PCs as eigenvectors and their corresponding coefficients as eigenvalues (Troje, 2002) or weightings (Young & Reinkensmeyer, 2014). A detailed mathematical account of the steps for performing PCA is outside of the scope of this paper, but tutorials have been well documented in existing literature (Daffertshofer et al., 2004; Federolf et al., 2014; Federolf, 2016; Forner-Cordero et al., 2005; Shlens, 2014).

Since each PC is a linear combination of the original data, the PCs and their corresponding coefficients can be recombined to reconstruct the data. Therefore, it is common to find studies that use PCA as a dimension reduction technique, finding the number of components required to reconstruct a chosen threshold of total variance, ranging anywhere from 80% (Walton, 2016) to 95% (Warmenhoven et al., 2019), depending on the study. Many human movements can be modeled to close to 90% accuracy using three to five components, provided the movements are restricted to certain planes and include a low number of joints, such as elbow flexion and extension, as in juggling (Zago et al.,2017a), knee and hip flexion and extension, as in downhill skiing (Federolf et al., 2014), diving from a diving board (Young & Reinkensmeyer, 2014) or performing a squat (Buchman-Pearle, 2021). In these cases, the closer the movement follows the ideal trajectory of the task trajectory without introducing random variation related to learning, motor dysfunction, or noise in the sensorimotor system, the greater amount of variance can be explained by the first or sometimes first and second components. Smaller components are thought to be more closely related to random variation, outside 'ideal' task performance (Forner-Cordero et al., 2005). These properties are used by researchers as indicators of the degree of organization in the movement and they can be used to gain insight into the degree of coordination across measured variables in the moving system.

5.1.3 Existing Research Using PCA to Study Musicians' Coordination Characteristics

Describing characteristics of the variation in motion capture data from pianists using standard PCA could provide researchers with insight into coordination characteristics by quantifying underlying characteristics of movement variation contributing to the total variation in motion capture data. PCA may also provide a means of tracking the stability of coordination characteristics over time to determine if movement retraining interventions lead to changes in pianists' typical coordination characteristics. PCA has already been used in some previous studies on musicians' movement. For example, Walton (2016) used PCA to study inter-personal coordination characteristics between two improvising musicians. The researcher used a wireless motion tracking system to track the head and arm movements of the two musicians improvising together on digital keyboards. The improvisers were instructed to perform in different conditions that placed varying degrees of constraint on the rhythmic, melodic, and harmonic content of their improvisations. Then, PCA was used to determine the number of principal components required to describe 80% of the variance in the original dataset and to determine how much of the total variance could be accounted for by only the first and second principal components. The researcher hypothesized that as the two musicians' movements became more synchronized the overall variation in the dataset would diminish, and a greater amount of overall variance would be represented by the first two components. Similarly, fewer components would be required to account for 80% of the overall variance. Results showed that the musicians' movements varied more in playing conditions where they were given either a harmonic foundation for improvisation (defined chord progressions) or rhythmic foundations (a backtrack providing a regular rhythmic pattern). Performers' movements varied more intra- and inter-personally (with a larger number of PCs explaining 80% of the variance), when playing with swing beat back track compared to a drone back track. PCA performed on movement data from both performers simultaneously shows evidence that some elements of the performers' movements are synergistic.

Verrel and colleagues (2013) used PCA as a means of comparing coordination characteristics of the bowing movements of novice cellists and expert cellists. Novice cellists received twenty-minutes of introductory instruction in cello bowing. Both experts and novices performed a repetitive bowing task on an open "A" string to a metronome. Their arm, head, torso, and bow movements were tracked using an optoelectric tracking system. The motion capture data generated joint angles data for the shoulder, elbow, wrist, and fingers, that were submitted to PCA. Researchers examined the proportion of individual and total joint variance described by the first principal component by projecting the coefficient time series of the first principal component onto the space represented by the joint angles to create a partial reconstruction of the data. These reconstructions were compared to the original data. Results indicated that novice cellists used a movement strategy with less overall movement at the elbow and wrist and that less variance was accounted for in the first principal component for novice cellists compared to expert cellists. Further, the first principal component contained more variance related to the shoulder in novice cellists compared to expert cellists.

Gonzalez-Sanchez and colleagues (2019) applied PCA as a means of better understanding how movement anticipation and joint co-articulation is related to movement-fluency in musicians. Rather than applying PCA to motion tracking data, this study collected surface electromyographical data (sEMG) from three cellists and three drummers performing a repetitive task, starting at a slow tempo, and then gradually accelerating to a faster tempo (drummers performed alternating hand strokes on a single drum, while cellists performed repetitive bow strokes on a single string). sEMG sensors were placed on the upper trapezius, triceps, forearm flexors and extensors, and gastrocnemius for the drummers, and on the middle deltoid, upper trapezius, triceps, and forearm flexors/extensors for the cellists. The body and arm movements were tracked using an optoelectric system. The researcher hypothesized that smoother musical performances would be accompanied by a more proximal to distal profile in muscle activation during playing strokes. However, in practice the patterns of muscle activation described by the PCA results seemed to reflect unique inter-individual tendencies in the timing of muscular recruitment when playing the task. Participants' task performance was inconsistent, with some struggling to accelerate to the maximum tempo. This suggests that muscle activation patterns are influenced by inter-individual differences and expertise, which would require investigation in future research.

PCA has also been applied in a study of pianists' hand gestures (Tits et al., 2015). Using an optoelectric system, researchers tracked the hand movements of four pianists (three with extensive classical training and one with less training who played primarily pop music) playing excerpts from a collection of well-known pieces chosen to ensure that the pianists' hand explored a variety of gestures. This exploratory study revealed that PCA can be used to break complex hand movements into sub-components (eigenmovements) that are related to specific features, such as hand movements coupling vertically or horizontally, or opening and closing movements of the hand. They found that the number and characteristic of the subcomponents described by the PCA depended on the complexity and characteristics of the musical patterns in the musical pieces. They also found that fewer components were required to describe 95% of the variation in the data for the pianist with less training and classical background compared to the three pianists with extensive classical training. Although speculative due to the small sample size, this finding suggests that future research should consider the possibility that coordination characteristics described by PCA may be sensitive to varying levels of expertise.

Furuya and Soechting (2012) further examined expert pianists' hand movements using PCA to study how tempo (playing speed) affected finger coordination characteristics. They tracked motion of joints in the hands of 5 expert pianists (all who had won performance prizes at international or national competitions) performing thirty excerpts from musical pieces (right hand only), each requiring different fingerings and keyboard locations. Pianists performed these excerpts at a prescribed tempo and as fast as possible. Results of this study revealed three distinct patterns of finger movement coordination that remained consistent, despite changes in tempo/playing speed. The results of this study show that independent control of fingers remains consistent across tempi for highly trained pianists.

Finally, a team of researchers incorporated PCA into their analysis of pianists' movements in pursuit of a strategy for comparing expressive gestures of different pianists playing the same piece to see how pianists' body gestures relate to their expressive intentions (Buck et al., 2013; MacRitchie et al., 2013). In this study, nine highly trained pianists were recorded using Vicon motion capture while performing two Chopin Preludes (Op. 28, Nos. 6 and 7). Passive markers were placed on the head, shoulders, arms, wrists, and spine, according to a previously described upper-body motion capture protocol (Cutti et al., 2005). PCA was used to create unique motion profiles for each pianist by linearly combining principal components required to account for 90% of the overall variance. This data reconstruction was plotted on a time scale that normalized variation in tempo and aligned the performances according to the beginning and ending of musical phrases. This allowed researchers to visually examine different frequency content (peaks and valleys) in the patterns represented by the PCA reconstruction to relate features of the plots with musical phrases and to compare characteristics across participants. By studying the local maxima in each phrase, the researchers noticed that each pianist generated their own unique patterns of gestural movements. However, most pianists' movements appeared to be related to the timing of musical structures, such as phrase boundaries or harmonic shifting. Some pianists' gestural body movements appear to be coordinated with larger structural features of the piece, shifting at structural boundaries such as the beginning of a new section, while others appear in reaction to smaller structural features of the piece, such as the beginning of individual phrases or measures of music. This study suggests that pianists' coordination characteristics are influenced in part by their understanding of the underlying musical structures.

The preceding studies indicate that researchers studying musicians' movement have found distinct applications for using PCA to gain insight into performer's movement characteristics. Existing literature suggests PCA is useful in identifying movement features unique to an individual performance or performer, or for comparing movements between groups expected to exhibit large differences in performance ability, such as comparing novice to experts. However, existing research has not yet explored if the information about motion capture data variation provided by standard PCA is suitable for tracking the consistency of musicians' movement over repeated measurements of defined musical tasks, or if it is sensitive enough to detect subtle changes to coordination characteristics that may result from movement retraining interventions. Based on existing findings, it is valid to hypothesize that a higher overall number of PCs explaining a threshold of total variance may correlate with a higher number of biomechanical degrees of freedom in a pianists' performances. Factors that influence how degrees of freedom are organized in human movement include: (1) level of expertise, as experts have learned to recruit a variety of degrees of freedom flexibly and automatically to execute a performance (Gautier et al., 2009; Zago et al., 2017b); (2) task complexity, as novice performers may freeze degrees of freedom when executing a complex, unfamiliar task (Verrel et al., 2013; Wu & Song, 2017); (3) performance conditions, as performers may freeze degrees of freedom when feeling high pressure to perform (Higuchi et al., 2002); (4) amount of task rehearsal/practice, since a performer's movements will change over time as they become more familiar with the task (Vereijken et al., 1992), and (5) performers adopting an internal or external focus of attention, since research has shown that maintaining an external focus on the effects of a movement may result in more automatic organization of movements (Wulf et al., 2001). It is possible that movement retraining interventions may influence the pianists' recruitment of degrees of freedom, but current research does not provide evidence supporting the hypothesis that standard PCA output values fluctuate in response to changes in these listed factors, or that changes in PCA output values can be explained by the mechanism of changes in the recruitment of biomechanical degrees of freedom. Furthermore, current research does not address the question of whether standard PCA output values are sufficient on their own to distinguish coordination characteristics in situations where many sources of variation are layered in the data and where movement differences are expected to be subtle, as would be the case when studying how movement retraining interventions influence cross-body coordination characteristics of pianists performing complex piano tasks.

5.2 Research Questions and Hypotheses

This study seeks to determine if standard PCA output values are useful for detecting differences in the variation characteristics motion capture data between different pianists performing musical tasks of varying complexity in repeated trials. Differences in variation characteristics identified using PCA may point to underlying differences in coordination characteristics that may be related to the level of task complexity, the degree of experience with the task, or to inter-individual differences in movement. In this paper, we use the term 'standard PCA' to refer to the practice of conducting PCA on a data matrix comprising columns corresponding to each of the x, y, and z motion capture trajectories from each anatomical marker, simultaneously. The data is not pre-processed outside of standard practices such as mean centering or normalizing to a standard deviation of one. Standard PCA output values chosen for this study include (1) the number of PCs required to describe 90% of the overall variance; (2) the percentage of overall variance described by the first three PCs; and (3) the number of PCs accounting for 2% or greater overall variance in the data set. There is no universal protocol for establishing an ideal threshold of variance that would have to be explained for an accurate reconstruction of the task. We chose 90% as the threshold, since in literature the thresholds range from 80% to 95%, with 90% being a common choice (Warmenhoven et al., 2019). By choosing a high threshold of variance we sought to include smaller components in the list (those accounting for a smaller amount of the overall variance), which may account for important performance details in the complex movements required in piano performance. We chose to record the amount of variance explained by the first three PCs, since existing literature indicates that many simple movements can be reconstructed to close to 90% accuracy within the first three to five components (Forner-Cordero et al., 2007; Zago et al., 2017a; Zago et al., 2017b). Less concentration of the variation in the early components is an indicator of higher degree of data complexity, arising either from overlapping sources of variation, or greater amounts of noise in the data. Noting the number of PCs greater than 2% is not a measure found in existing studies, but it was included in the present study since we anticipated that smaller components may reflect variation related to real movement features due to the inherent complexity of the performance movements. A higher number of small components comprising the 90% threshold would indicate greater variability in the movement.

To learn more about the suitability of PCA in this application, we compared standard PCA output values from four different tasks of varying task complexity among 5 different pianists to test whether PCA helped distinguish subtle differences in movement patterns brought about by (1) differences in musical task complexity; (2) differences arising from learning effects resulting from practicing the task; and (3) inter-individual differences between pianists. We hypothesized that the degree of task complexity may influence pianists' coordination patterns, since pianists may be free to recruit more degrees of freedom in their movement while performing a very simple or very familiar task. We hypothesized that performing a more complex musical task may elicit greater restriction of degrees of freedom as pianists devote greater cognitive resources to executing the more complex tasks, and that the resulting coordination differences between simpler and more complex tasks would be detectable by the basic PCA indicators. However, we hypothesized that standard PCA output values may not be sensitive to changes to coordination due to learning/practice effects in this study, since the tasks were performed by skilled pianists who were able to quickly learn to play the tasks with minimal practice time before or between data collection sessions, and any changes to coordination due to learning effects would likely be slight. Finally, we hypothesized that standard PCA output values may be sensitive to differences in coordination characteristics resulting from individual pianists' unique approaches to playing, since all pianists were free to choose their own tempos and would apply their own technical approaches to playing the tasks. We expected that the natural differences in individual playing approaches may be substantial enough to be reflected in different standard PCA output values for a given task. Results of this preliminary study will give a first indication of the suitability of standard PCA procedures for detecting subtle differences in movement patterns that may arise from movement retraining interventions and direct future research toward possible solutions for increasing the sensitivity of PCA to subtle differences in pianists' coordination.

5.3 Methodology

Five advanced pianists (three males, two females, ages 24-58, mean age: 37 years) participated in three motion capture sessions over three weeks, spaced one week apart. Prior to data collection, pianists changed into shorts and a tight-fitting black athletic top (figure 5.1). Twenty-two reflective markers were positioned on anatomical landmarks on the participants' head, shoulders, spine, hands, arms, sacrum, and pelvis (table 5.1). The markers on the hands, arms, shoulders, and C7 were fastened directly to the skin with adhesives. The four head markers were fixed to a headband participants wore around their heads. The spine and sacrum markers were fastened using medical tape to fix strong magnets over the specified vertebrae. The reflective markers were then attached using magnets outside of the athletic top to ensure the markers stayed centered over the intended vertebrae despite movements of the shirt during performance trials. The two pelvic markers on the bilateral posterior superior iliac spines (PSIS) were fixed using adhesive stickers on the exterior of the clothing. Table 5.1 presents a full list of the location of anatomical landmarks.

Figure 5.1

Placement of Anatomical Markers

Table 5.1

Anatomical Landmarks for Placement of Reflective Markers

Region	Anatomical landmarks
Head	Four markers on head band: (two anterior skull, two posterior skull)
Spinal vertebrae	C7 T3 T7 T11 L3 Sacrum
Pelvis (bilateral)	PSIS
Arms (bilateral)	Acromion Lateral epicondyle of the humerus Styloid process of the ulna Styloid process of the radius Distal aspect of the third phalanx (just proximal to the metacarpal phalangeal joint of the third digit)

Once the anatomical markers were positioned, pianists warmed-up on the piano for five minutes prior to data collection. During this time participants played whatever they wished to become habituated to the lab environment. Many participants chose to warm up by practicing the prescribed musical tasks. 3D motion capture trajectories were collected from the 22 anatomical markers using a nine-camera Vicon system at a frequency of 100 Hz. MIDI (Musical Instrument Digital Interface) data was collected from the Yamaha P-255 digital piano. At each data collection session pianists performed the following battery of four musical tasks chosen to reflect different levels of technical and musical complexity. Notated scores of these musical tasks and detailed performance instructions can be found in Appendix A.

List of musical tasks:

1) Two-note slurs (easy technical task): A sequence of five notes played by the right and left hand in contrary motion. Adjacent pairs of notes are connected smoothly, *legato,* and the pianist allows the keys to lift completely at the end of each connected pair, leaving a short gap in the sound. This task was selected to be easy to execute with low complexity. Pianists were able to successfully play this task with no prior preparation.
2) Symmetric Fifths (difficult technical task): A sequence of blocked/harmonic fifths played by the right hand and left hand symmetrically, retrieved from exercise 17b in *Mikrokosmos, Volume II* (Bartók, 1987/1940). Each fifth is played with the first and fifth finger (thumb and pinky). The fifths are played detached (non-*legato*). This task is difficult to sight-read accurately due to the frequent use of accidentals (sharps and flats) and the changing direction of the notes. Most pianists would have to practice this task to perform confidently, and they would likely improve after repeated performances.
3) Alberti Bass (intermediate technical task): The first four bars contain an alternating eighth note pattern in the left hand while the right hand plays blocked, three-note chords. The last four measures invert the pattern, with the right hand playing an alternating note pattern while the left hand plays blocked chords. The Alberti Bass pattern of alternating notes is familiar to experienced pianists and highly automated from years of practice, especially when the left hand is executing the alternating pattern. However, inverting the pattern and changing the hands' roles from bar four to

bar five requires focus and practice for smooth execution. This change may destabilize pianists' coordination momentarily as they adjust from one pattern to the next.

4) Waltz (intermediate musical task): Pianists perform the piece *Valse Mignonne* composed by Henryk Pachulski (2010/1906) twice, with a break between the first and second performances. Unlike the first three tasks, the Waltz is a musical piece rather than a technical exercise, and therefore opens itself to unique interpretations in phrasing and dynamics that depend on the performer's expressive intentions. This is a simple, lyrical Waltz that most experienced pianists will find easy to play after some preparation. However, some pianists may find parts when the melody is transferred to the left hand more challenging.

5.4 Analysis

Data was analysed using MATLAB™ software to report: (1) the number of PCs required to describe 90% of the total variance; (2) the number of PCs describing 2% or more of the total variance; and (3) the variance described by the first three PCs. We applied the PCA command in MATLAB to all 66 movement trajectories from 22 anatomical markers (each marker represented by an x, y, z axis trajectory). The raw movement trajectories were not filtered, smoothed, or normalized, but the data was mean-centered. We did not filter the data to avoid removing meaningful variation in the data. For instance, we noted that for some musical tasks the frequency of note presses exceeded the frequency thresholds of many common filtering strategies in biomechanics. By not filtering we sought to preserve small components that may contain meaningful information about participant specific or task specific variation characteristics. Furthermore, since postural angles or secondary variables calculated from position, such as velocity or acceleration were not computed in this study, any measurement error arising from the motion capture system would not be amplified from additional computations.

The MIDI data and the motion trajectory data were time-synced using a manual MIDI signal created by placing a reflective marker on the lowest key of the piano and requiring the pianist to press it once immediately before and after playing the musical tasks. PCA was conducted on motion trajectory data from the time of the first MIDI note performed in the task to the last MIDI note performed. For tasks 1 to 3, the task ended on the time-off of the last note of the seventh repetition of the task. For task 4, the task ended when the last notes of the piece were released according to MIDI data. Movement from before or after the performance of the task itself was not included in the PCA.

The MIDI data was processed using custom MATLAB software to report MIDI note duration, inter-onset-interval of the notes, and note velocity. Note duration values report how long a key was pressed, while inter-onset interval reports the time between consecutive key presses. Both values give information about the consistency of the musical tempo and rhythm. The note velocity values report the speed of the key descent for a MIDI event and give information about note loudness. As note velocity increases, the perceived loudness of the note increases. Note velocity measures give information about the pianists' musical choices for voicing (which notes were played loudest out of a group of simultaneous key presses), balance (which parts of the musical lines are emphasized by playing them louder relative to other lines occurring simultaneously) and dynamic shaping (how the pianist changes the loudness of the notes played over time.) The MIDI data were analysed by separating the data for the two hands. In the case of the Symmetric Fifths, the MIDI values were separated based on the four layers of notes occurring simultaneously for each chord (the top and bottom note of the right hand were separated, and the top and bottom note of the left hand were separated). For the Alberti Bass task, the MIDI representing the faster moving eighth notes were reported separately from the solid chords, and the solid three-note chords were reported as three separate layers, one for the top, middle, and bottom notes of each solid chord. MIDI values were not separated based on hand or musical layers for the Waltz task because of difficulties posed by the greater variety of note values and overlapping note registers between the right and left hand. Instead, a labeling technique was used to visually identify longer and shorter notes within the sequence to look for trends in loudness across the performance. Additionally, MIDI characteristics were used as a means of creating a visual diagram of the pitch and rhythmic data that could be visually compared to qualitatively assess how the variation features of the musical data (such as frequency of note depression, repetitions of sub-units in the musical task, and repetition of the entire musical task) related to the visual features of the PCs. These visually identified relationships facilitate discussion points for further research and are not intended to be used to make quantitative conclusions about the data.

5.5 Results

Results of this study suggest that standard PCA output values adapted from other studies on human movement are not sensitive enough to account for differences in pianists' movement between different tasks or across repeated performances of the same task on different days. No clear trends in the number of PCs appeared across trials for any tasks or participants, however, PC waveforms suggest some pianists' movement characteristics varied between trials for a given task. Biomechanical interpretation of PC waveforms is not possible because the current approach does not permit analyzing task-related variation independently from intra-individual variation related to biomechanical choices.

5.5.1 Comparing PCA Results Between Technical Tasks of Varying Complexity Across all Participants and Trials

The standard PCA output values are not sufficient on their own to distinguish between the different musical tasks chosen for this study. We hypothesized that standard PCA output values might react to changes in the variability characteristics of the movement data across tasks of varying levels of complexity. It was expected that pianists' movements may be more complex and varied during the performance of very simple or familiar tasks, such as the two-note slurs, since simpler tasks require fewer cognitive resources and may permit greater flexibility in the recruitment of degrees of freedom (Chang et al., 2020). We hypothesized that the increased availability of degrees of freedom for simpler and familiar tasks would be reflected in the PCA results by higher numbers of PCs required to explain 90% of the variance, and a smaller amount of overall variance explained by the first three PCs, meaning more of the overall variance would be explained by smaller PCs. However, as can be seen in table 5.2, the standard PCA output values were very similar between the more demanding Symmetric Fifths task and the familiar Alberti Bass task. A similar number of PCs is required to describe 90% of the variance of these two exercises (on average 6.4 and 6.3, respectively). They also had a similar number of components representing 2% or greater total variance (on average 6.9 and 6.7, respectively). The first three components described a similar amount of the overall variance (on average 73.3% and 74.4%, respectively). The standard PCA output values suggest that two-note slurs require a slightly higher number of PCs to describe 90% of the variance overall, with an average of 6.9 PCs required to describe 90% of the variance (about 0.5 PCs higher than the other tasks). There also appeared to be, on average, a greater number of small components for the two-note slur task, with a slightly higher number of components representing 2% or greater total variance (7.5). The average percentage of total variance described by the first three PCs was also about 5% lower for the two-note slur task compared to the Symmetric Fifths and Alberti Bass exercises.

Table 5.2

Average Standard PCA Output Values for Technical Piano Tasks of Varying Complexity Across All Participants and Trials

Task	Difficulty	Average No. of PCs required to describe 90% of total variance	Average No. of PCs describing 2% or more of total variance	Average variance explained by the first three PCs (%)	Minimum variance explained by the first three PCs (%)	Maximum variance explained by the first three PCs (%)
Two-note slurs	Easy	6.9	7.5	69.7	60.7	76.8
Symmetric Fifths	Difficult	6.4	6.9	73.3	68.3	78.6
Alberti Bass	Moderate	6.3	6.7	74.4	69.3	80.3

It is possible that the higher number of smaller PCs for the two-note slur exercises resulted from the lower cognitive and motor demands of this simple musical task, but the difference is small and the sample size is not large enough to determine if this is significant. The Symmetric Fifths and Alberti Bass tasks both placed greater demands on the cognitive and motor systems due to greater independence of movement between the two hands and higher sight-reading demands for decoding the notes on the page. It is possible that the greater cognitive and motor demands of these two tasks resulted in freezing more degrees of freedom and therefore less motor variability. However, the similarity of the standard PCA output values across the tasks chosen for this study suggest any difference in basic PCA indicators between the tasks of varying complexity chosen for this study is too subtle to show up in the standard PCA or that differences may be present but are not detectable using the standard PCA. The similarity of results across the different tasks suggests that testing the hypothesis that simpler tasks lead to greater degrees of freedom, and therefore greater motor variability that is detectable in using standard PCA would require an extremely large sample size. The procedure for applying PCA to the motion capture data of this study is not sensitive enough to indicate the possibility of differences in coordination characteristics between pianistic tasks of different complexity if those differences do exist. The current data is insufficient to support relationships between the number of principal components, degrees of freedom, task complexity, and the experimental protocol.

5.5.2 Comparing PCA Results Across Trials One, Two, and Three for Technical Piano Tasks of Varying Complexity

We expected that pianists' coordination characteristics may change over the course of trials one, two, and three due to learning effects from practicing the task and becoming more accustomed to the lab environment and data collection procedures, especially for more difficult tasks which were expected to become easier with practice. However, we hypothesized that any changes due to learning/practice effects would be too subtle to be detected in the basic PCA values. As shown in table 5.3, the results suggest that basic PCA indicators do not appear to be sufficient to distinguish between trials one, two, and three for the tasks examined in this study.

Table 5.3

Comparing Average Standard PCA Output Values Across Trials 1, 2, and 3 for Technical Piano Tasks of Varying Complexity Across All Participants

Task	Difficulty	Trial	Average No. of PCs required to describe 90% of total variance	Average No. of PCs describing 2% or more of total variance	Average variance explained by the first three PCs (%)
Two-note slurs	Easy	1	7.0	7.6	68.8
		2	6.8	7.0	70.9
		3	6.8	7.8	69.2
Symmetric Fifths	Difficult	1	6.6	7.0	72.1
		2	6.4	7.0	73.7
		3	6.2	6.8	74.1
Alberti Bass	Moderate	1	6.2	6.8	74.1
		2	6.4	6.6	74.7
		3	6.4	6.8	74.5

We expected increased task experience to have the least impact on the simple two-note slur task, since participants likely found that simple to perform, with very little room for improvement or variation across trials. We expected the movements to change more due to practice or learning effects for more complex tasks, such as the Symmetric Fifths, which were more difficult to play correctly the first time. We also expected little change due to practice or learning effects to the familiar Alberti Bass pattern, since these movements are highly automated in trained pianists. However, none of the average standard PCA output values display strong trends suggesting either an increase or decrease across trials that could be plausibly linked to possible learning effects. A slight decrease in the total number of PCs required to describe 90% of the variance and in the number of components describing 2% or greater variance did appear across trials 1-3 for the more difficult Symmetric Fifths task. This aligns with the results showing that the percent of variance explained by the first three components increased from 72.1% in trial 1 to 74.1% in trial three. Since fewer patterns explain a greater percentage of the overall variance as trials progress and the difficult task presumably becomes easier to play, these results suggest that the initial hypothesis that increased degrees of freedom due to increased expertise would correlate with a greater number of PCs required to explain most of the variance may be incorrect. This slight trend suggests that the opposite could be true; perhaps as the difficult task became easier, participants' movement strategies became more streamlined and contained less random variation resulting in a greater amount of the variance explained by fewer, more optimized patterns. Although a larger sample size would be required to statistically test these questions, the lack of clear trends in the preliminary results suggest that either the changes to movement patterns due to learning/practice effects were negligible for these tasks, or that PCA procedures applied in this study are insufficient for detecting subtle differences in movement that may arise due to learning effects.

5.5.3 Comparing PCA Results Between Individual Pianists

We hypothesized that standard PCA output values may reflect differences in coordination patterns between pianists, who would each bring their own unique playing approaches to the tasks. Comparing the standard PCA output values for the three principal tasks across participants suggests that they may be slightly sensitive to differences in overall pianistic ability, but do not appear to provide a robust means of distinguishing coordination characteristics between individual pianists. For example, tables 5.4, 5.5, and 5.6 display that participant 5 always scored the maximum values of the PCs describing 90% variance and the number of PCs describing 2% or greater variance for one or more trials for all tasks. The only exception occurred in the Symmetric Fifths task, in which participant 5 scored the maximum value of 8 in the second trial for the number of components required to describe 90% of the variance, while participant 3 scored the maximum value of 8 for the number of components describing 2% or greater variance for trial two. Anecdotal review of the audio-visual data and demographic information of participant 5 suggests they found the musical tasks more difficult to play than the other four participants, as was reflected by their choice of slower tempi, more frequent note errors, and more frequent pauses compared to other participants. It is likely that some aspects of participant 5's movement differed compared to pianists who found the tasks less challenging, but the standard PCA output values on their own are insufficient to begin to speculate on possible coordination characteristics underlying those differences. Furthermore, these preliminary results suggest that the pianist who found the excerpts more challenging tended to have higher scores for the 90% and 2% indicators, which contradicts the hypothesis that the number of PCs required to describe 90% of the variance and the number of PCs describing 2% or greater variance would be lower for more complex tasks due to freezing degrees of freedom.

Table 5.4

Comparing Standard PCA Output Values Between Participants Across Trials 1, 2, and 3 for the Easy Two-Note Slur Task

Participant	Trial	Average No. of PCs required to describe 90% of total variance	Average No. of PCs describing 2% or more of total variance	Average variance explained by the first three PCs (%)
1	1	6	6	76.5
	2	6	7	76.8
	3	6	7	69.0
	Average	6.0	6.7	74.1
2	1	7	8	69.1
	2	6	7	76.6
	3	6	8	74.7
	Average	6.3	7.7	73.5
3	1	8	9**	61.6
	2	7	7	61.4
	3	7	8	66.8
	Average	7.3	8	63.3
4	1	6	7	70.7
	2	6	6	74.5
	3	6	7	75.1
	Average	6	6.7	73.4
5	1	8	8	66.2
	2	9**	8	65.1
	3	9**	9**	60.7
	Average	8.7	8.3	64.0

Note. ***marks the occurrences of the maximum value of PCs required to describe 90% of the total variance and the number of PCs describing $\geq 2\%$ of the total variance.*

Table 5.5

Comparing Standard PCA Output Values Between Participants Across Trials 1, 2, and 3 for the Difficult Symmetric Fifths Task

Participant	Trial	Average No. of PCs required to describe 90% of total variance	Average No. of PCs describing 2% or more of total variance	Average variance explained by the first three PCs (%)
1	1	6	7	75.0
	2	6	6	78.1
	3	6	7	76.3
	Average	6	6.7	76.3
2	1	7	7	68.3
	2	6	7	68.6
	3	7	7	69.7
	Average	6.7	7	68.8
3	1	7	7	69.7
	2	7	8**	72.9
	3	6	7	71.8
	Average	6.7	7.3	71.4
4	1	6	7	78.2
	2	5*	7	78.6
	3	6	7	77.1
	Average	5.7	7	78.0
5	1	7	7	69.4
	2	8**	7	70.2
	3	6	6	76.0
	Average	7	6.7	71.9

Note. ** *marks the occurrences of the maximum value of PCs required to describe 90% of the total variance and the number of PCs describing* $\geq 2\%$ *of the total variance.* * *marks the occurrences of the minimum value of those variables.*

Table 5.6

Comparing Standard PCA Output Values Between Participants Across Trials 1, 2, and 3 for the Intermediate Alberti Bass Task

Participant	Trial	Average No. of PCs required to describe 90% of total variance	Average No. of PCs describing 2% or more of total variance	Average variance explained by the first three PCs (%)
1	1	6	7	69.4
	2	6	7	70.7
	3	6	7	71.1
	Average	6	7	70.4
2	1	7	7	72.3
	2	7	7	72.7
	3	7	7	71.3
	Average	7	7	79.8
3	1	6	6	80.0
	2	6	7	79.1
	3	6	6	80.3
	Average	6	6.3	79.8
4	1	5*	7	78.0
	2	5*	5*	80.3
	3	5*	6	78.1
	Average	5	6	78.8
5	1	7	7	71.1
	2	8**	7	70.8
	3	8**	8**	71.7
	Average	7.7	7.3	71.2

*Note. ** marks the occurrences of the maximum value of PCs required to describe 90% of the total variance and the number of PCs describing ≥ 2% of the total variance. * marks the occurrences of the minimum value of those variables.*

However, looking broadly at the values in table 5.4, 5.5, and 5.6, the differences in the PCA values for participant 5 compared to the other participants were not dramatic. Considering that the substantial difference in performance ability between participant 5 and the other participants was evident from anecdotal review of the audio-visual data, the results demonstrate that standard PCA output values are not a useful measure for detecting differences in the coordination characteristics of different pianists, even in cases where the differences in performance ability are evident from fluctuations in tempo and note errors. Basic PCA indicators may be able to detect slight statistical differences in the variation of motion capture data relating to differences in coordination characteristics in a study with a very large sample size, as has been done in previous studies on elite and novice athletes (Ross et al., 2018). Conducting a large-scale study of this nature is inconsistent with the goal of the current study, which seeks to understand how individual pianists' coordination characteristics evolve over time in response to movement retraining intervention. It would be impossible to acquire the requisite data to test these differences statistically with the current analysis approach because the participants would have to play the same tasks hundreds of times to achieve statistical power. Our results suggest that the standard PCA values chosen for this study are unsuitable for detecting variation characteristics related to unique coordination characteristics of individual pianists over repeated trials, or for measuring potential changes to coordination characteristics resulting from movement retraining interventions.

5.5.4 PCA Results from the Waltz Task

We expected that the standard PCA output values from the Waltz task could not be meaningfully compared with the results from the other three tasks because the task characteristics of the Waltz were more varied and complex. We expected there would be more variation in the pianists' coordination patterns in the Waltz compared to the simpler tasks because the Waltz contains greater variation in pitch, note length, and note loudness, and because the two hands were required to play musically distinct patterns. We anticipated that the greater complexity of this task would be reflected in the standard PCA output values by a higher number of PCs required to explain 90% of the variance, and a higher number of components describing 2% or greater variance. We also hypothesized that a greater number of small PCs would be required to account for the greater variation in this task.

Results show that this is not the case. In fact, the standard PCA output values of the Waltz were very similar to the results for the first three tasks. As seen in figure 5.2, the first three PCs described an average of 74% of the overall variance for the Waltz task, which was very similar to the amount explained by PCs 1-3 in the other tasks (tables 4, 5, 6).

Figure 5.2

Percentage of Variance Described by PCs 1-3 for Waltz 1 and Waltz 2 Across Three Trials

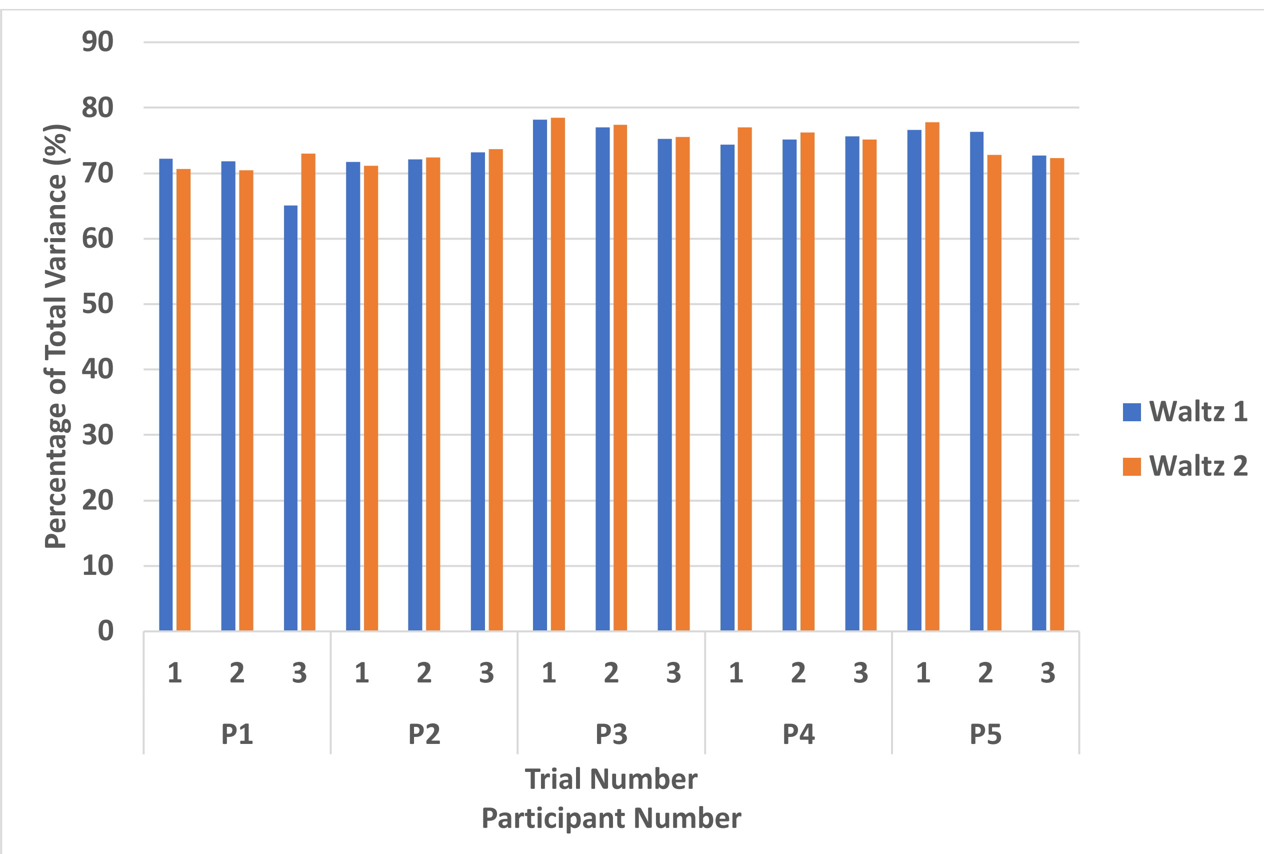


Table 5.7 shows that the average values across the three trials for the number of PCs required to describe 90% of the variance, and the number of PCs ≥ 2% for the first and second were very similar for the Waltz tasks (repetitions 1 and 2) and the other tasks. The lack of noticeable difference between the average PCA values for the simpler and more repetitive technical tasks and the more musical tasks with many different melodic and rhythmic patterns comprising the right hand and left-hand parts is surprising. Even with such a great difference in pattern complexity between the musical Waltz task and the three simpler technical tasks, the PCA results are relatively uniform across tasks, trials, and pianists. These results suggest that applying standard PCA using the established practice of examining basic PCA indicators is only able to give a very high-level overview of variation that quantifies coordination patterns of piano playing in general. It is unable to provide insight into details about coordination patterns pertinent to specific musical tasks, individual performers, or how performance movements fluctuate over time.

Table 5.7

Comparing Average Standard PCA Output Values Across Trials 1, 2, and 3 for Waltz and Technical Tasks Across All Participants

Task	Trial	Average No. of PCs required to describe 90% of total variance	Average No. of PCs describing 2% or more of total variance
Two-note slurs	1	7.0	7.6
	2	6.8	7.0
	3	6.8	7.8
Symmetric Fifths	1	6.6	7.0
	2	6.4	7.0
	3	6.2	6.8
Alberti Bass	1	6.2	6.8
	2	6.4	6.6
	3	6.4	6.8
Waltz 1	1	6.2	6.6
	2	6.2	6.8
	3	6.6	7.0
Waltz 2	1	6.4	6.8
	2	6.4	7.0
	3	6.6	6.6

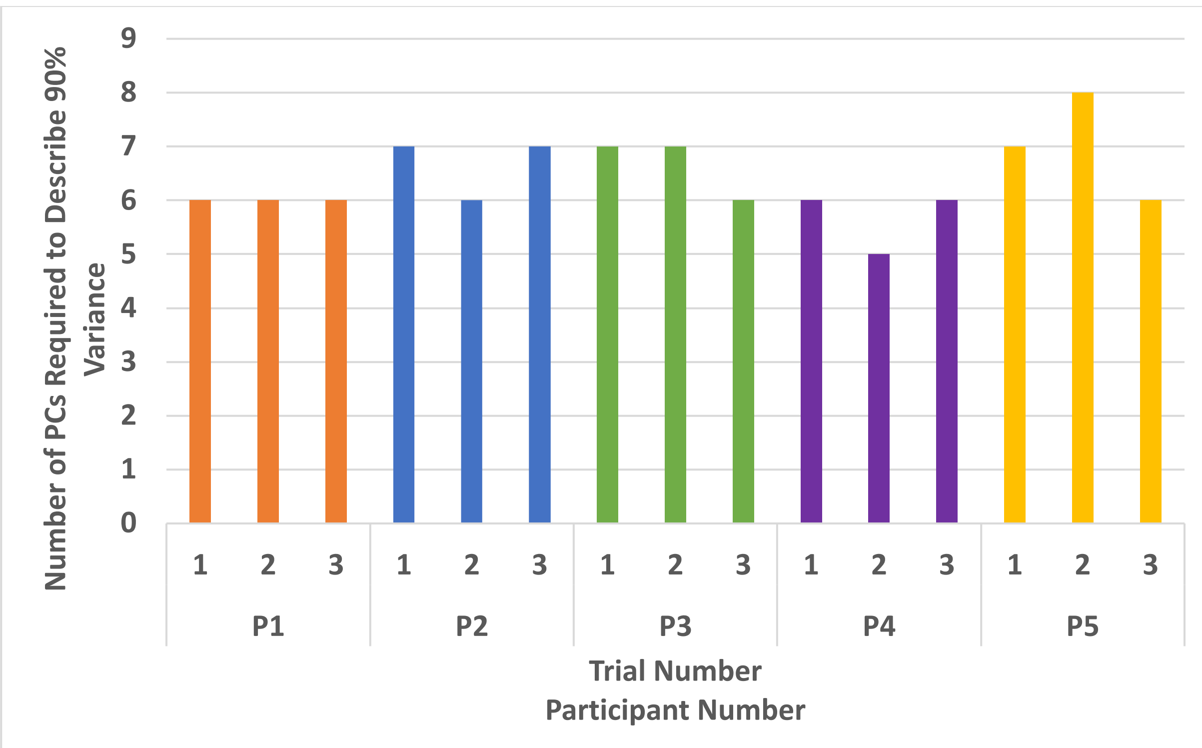
5.5.5 Comparing MIDI and PCA Results for Evidence of Performance Variation Across Trials

The results of this study suggest that basic PCA indicators are not sensitive enough to track differences in coordination characteristics that may arise due to differences in task complexity, possible learning/practice effects across trials, and inter-individual differences in piano task performance for the tasks selected for this study. However, examining sound characteristics in the MIDI data suggests that there may have been measurable differences occurring between the performances that were not reflected in the standard PCA results. This can be exemplified by comparing the PCA results and the MIDI note velocity results for the Symmetric Fifths exercises. Figure 5.3 displays that all five pianists required a similar number of

PCs to describe 90% of the variance for this task, ranging from five to eight components, depending on the pianist and the trial. It is also evident that there were no observable trends in the number of PCs describing 90% over the three trials. For instance, while participant 1 maintained six components across three trials, the other fluctuated by one or two components from trial to trial (figure 5.3).

Figure 5.3

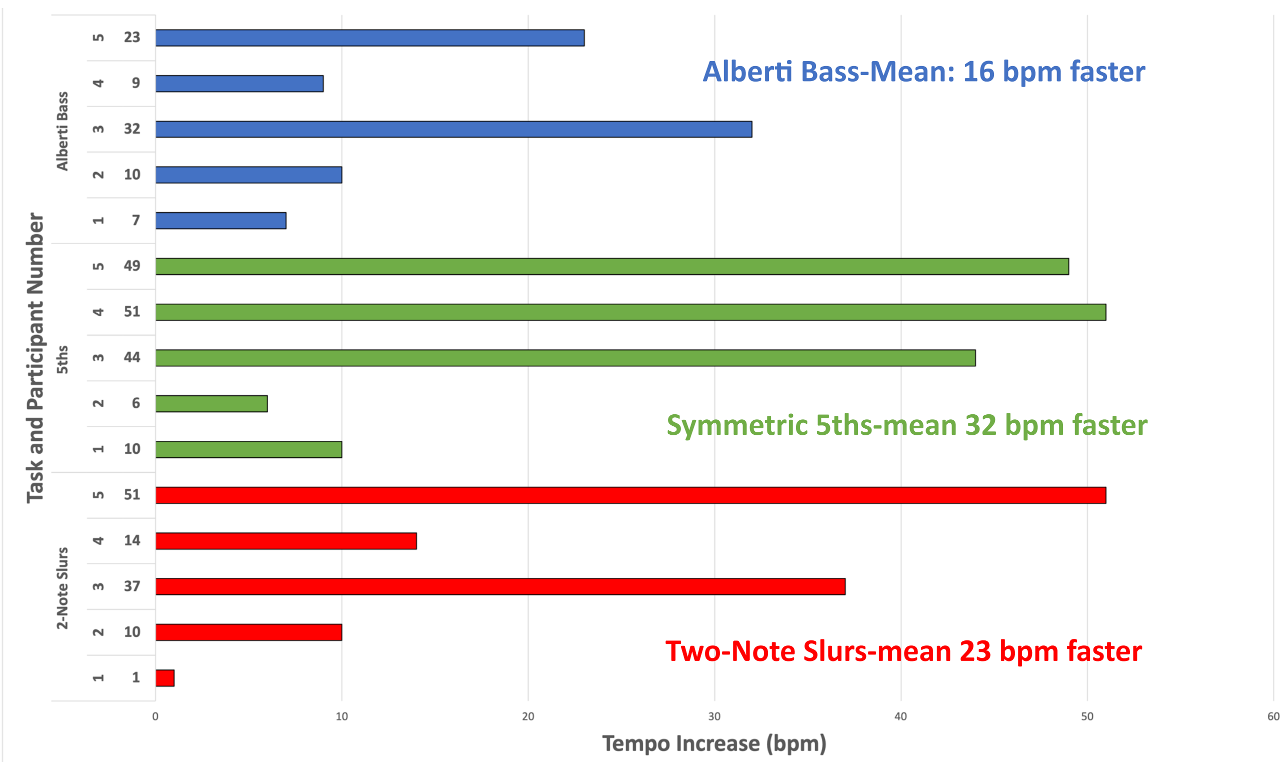
Average Number of PCs Required to Describe 90% of the Variance in Symmetric Fifths Across Three Trials



Even though the PCA results were somewhat uniform across pianists for this task, the MIDI data hinted that in fact there were meaningful differences in performance between pianists and across trials that the PCA could not detect. Results from the MIDI data suggest that participants were improving or at least finding the all the tasks easier to play by the third session because tempos increased on all tasks for all participants on session three compared to session one. Figure 4 illustrates the tempo increases from session 1 to 3 were greatest for Symmetric Fifths exercise, which most people found the hardest to play initially. It is possible that some aspects of pianists' coordination characteristics may have differed as they performed the task at different tempi, however, if such differences occurred the PCA was not sensitive enough to detect them.

Figure 5.4

Tempo Increases from Trial One to Trial Three for All Technical Tasks

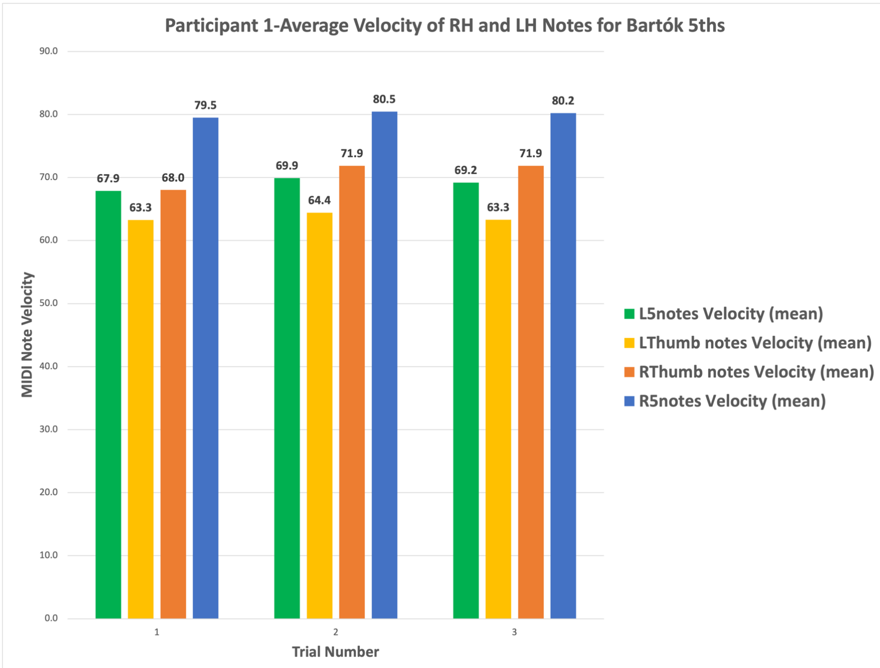


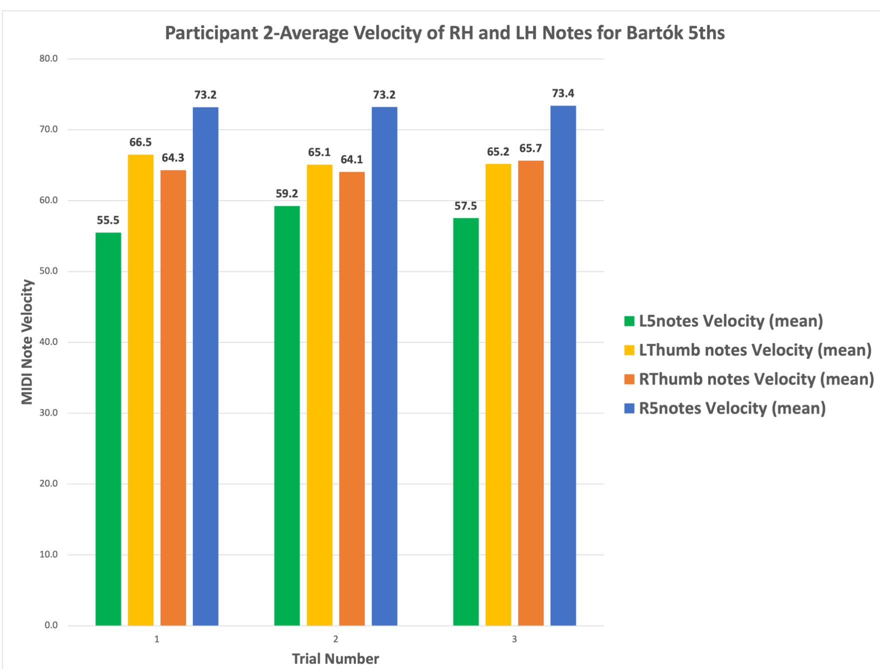
Note. *'Bpm' stands for 'beats per minute'. It is a measure of musical speed and defines the number of beats that occur in one minute of time.*

MIDI velocity results also hinted at inter-individual differences in pianists' strategies for playing the Symmetric Fifths task that were not reflected in the PCA of the movement data. For example, figure 5.5 shows the average note velocity of each of the four notes played in each chord during the Symmetric Fifths exercise for participant 1. The average velocity of their fifth finger (pinky) of the right hand, which was the highest note in the chord, is depicted in blue. The average velocity of their fifth finger of the left hand, which as the lowest note in the chord, is depicted in green. This shows that participant 1 consistently voiced the top note of the chord the loudest, while voicing the bass note slightly louder than the inner voices, perhaps attempting to find balance in the chord that highlights a perceived melody and bass line. By contrast, participant 2 consistently voiced the highest note in the right hand loudest and the lowest note in the left hand the softest.

Figure 5.5

Average MIDI Velocities of Right Hand and Left-Hand Notes in the Symmetric Fifths Task for Participants 1 and 2





These MIDI results suggest that participants 1 and 2 played the exercise differently, suggesting that there may be biomechanical strategies underlying their individual approaches to voicing the chords, since pianists control the loudness of notes by adjusting the movements of their hands and arms. However, since there is no biomechanical information in the MIDI data, we are unable to identify what characteristics in their movement may be accounting for the differences in their performances. Finger flexion movements were not measured for this study, but it is possible that aspects of coordination related to rotation of the distal and proximal radioulnar joints may have played a role in note velocity for this specific exercise. These MIDI examples suggest that in some cases performances were measurably different between pianists and trials. In its current application, the basic PCA procedures cannot give us insight into better understanding this or other movement details underlying inter-individual variation in piano task performance. The subsequent discussion outlines important reasons why this may be the case and suggests next steps in research that could increase PCA's ability to target meaningful movement variation related to coordination characteristics of pianists in future studies.

5.6 Conclusions

This investigation suggests that the standard PCA output values commonly used in other studies in human movement research are not sensitive enough to detect subtle differences in pianists' coordination characteristics that may result from different degrees of task complexity, inter-individual differences due to pianist-specific approaches to playing or learning effects resulting from increased practice of musical tasks. This suggests that standard PCA output values are unsuitable for tracking and measuring subtle differences in pianists' coordination characteristics that might result from movement retraining interventions. Reflecting on the reasons PCA failed to distinguish between performances in this study will help us better understand its limitations and discover if it may be possible to devise new strategies that address the limitations and optimize its application future studies on pianists' coordination characteristics.

There was not sufficient evidence to concretely address the hypothesis that lower task complexity and greater task familiarity would lead to increased degrees of freedom in the performers' movements due to lower cognitive demand. However, the trend showing a very slight decrease in the number of PCs required to describe 90% of the variance and in the number of PCs $\geq$ 2% for the more difficult Symmetric Fifths exercise from trial 1 to 3, combined with the MIDI evidence which shows that all pianists increased their tempo of this task from trial 1 to 3 suggests the opposite might be true; perhaps as a difficult task becomes easier, the movements become more consistent and less random, resulting in fewer variation patterns explaining a larger amount of the overall variance. Similarly, the evidence that participant 5 struggled the most with performing the tasks and nearly always had the highest number of PCs explaining 90% of the data and more PCs $\geq$ 2% for all tasks suggests that perhaps more novice performers may have more diversity in the underlying variation patterns comprising their movement. This could be due to the employment of more random movement strategies associated with learning, rather than purposeful movement strategies associated with expertise. Further testing with a larger sample size would be required to thoroughly investigate this hypothesis.

5.7 Discussion

Although the PCA results of the study did not identify variation characteristics in the motion capture data pointing to unique coordination characteristics or movement trends between pianists, or across tasks or trials, they do quantitatively confirm the hypothesis that variation in pianists' movements is inherently more complex and difficult to study when compared to other types of human movements that researchers have used PCA to study in the past. For instance, in many earlier studies applying PCA to human motion capture data, only two or three PCs were required to reconstruct the movement to 90% variance (Forner-Cordero et al., 2007; Zago et al., 2017a; Zago et al., 2017b). Our results show that the first three PCs generally account for around 70% of the overall variance, and that seven to eight components are required to reconstruct pianistic motion capture data to 90% for all tasks in this study. These results were similar for very simple tasks, like the two-note slurs, and for more complex and varied tasks, such as the Waltz piece. This suggests that a broad application of PCA to motion capture data of pianists describes high-level variation characteristics typical of pianists' movements in general without being able to comment with any specificity about coordination features related to individual pianists or tasks. In some cases where a substantial difference in movement occurs, PCA may provide researchers with evidence that *something* in the pianists' coordination may have changed. However, without further adjustments to the analysis, PCA cannot expose biomechanical details of *how* the movement changed, or how any changes may be related to certain sub-patterns in the musical tasks. This observation points to a further need to reflect on why PCA may have failed in this application and to consider if it might be possible to develop piano-specific procedures for applying PCA that can target variation patterns related to coordination characteristics that could be tracked and measured over time.

Although the current method of applying PCA to motion capture data appears unsuitable for tracking changes to pianists' coordination characteristics participating in movement retraining interventions, the results of this study can be used to highlight the importance of understanding the mathematical foundations of PCA as a means of studying variation in complex data sets. PCA is merely a means of transforming a data set to look at it from the perspective of vectors representing how the variables relate to each other. PCA simply identifies and ranks underlying variation features in a data matrix comprised of all the motion capture variables. In the present study, there are 66 variables (an x, y, z trajectory for each of the 22 anatomical markers). Each individual PC contains information all 66 variables from across the body at once. Therefore, when considering any potential biomechanical interpretations of PCA results, it is important to remember that individual PCs are not directly relatable to individual anatomical marker, body parts, or specific sub-features of the musical patterns. Since PCA merely transforms an existing data set, all sources of variation that contribute to data influence resulting PCs. On its own, PCA cannot discriminate between variation that may be meaningful to answering a research question, such as subtle variation in coordination characteristics of pianists in response to movement retraining interventions, or variation related to pre-existing patterns, such as the patterns related to the musical tasks themselves. In the case of music performance, the variation related to a fixed sequencing of pitches at specific rhythmic intervals dictated by the musical score means that a substantial source of variation analysed by PCA relates simply to task requirements, which are common to all participants. It is possible that variation related to task requirements may be the dominant form of variation in motion capture data of the performance of a fixed musical score. This fixed variation common to all participants may obscure any intra- or inter-individual differences in coordination characteristics and may also help account for the relative uniformity of standard PCA values reported across tasks and participants in this study. There are many different sources of variation contributing to the overall variation in motion capture data of pianists related to both task and biomechanical constraints that must be considered to make it possible to develop procedures for applying PCA that can more meaningfully target variation related to individual coordination characteristics and their fluctuation over time. Future research applying PCA as a tool for studying pianists' coordination characteristics requires researchers to develop frameworks that identify, categorise, and organize the different sources of variation layered into the motion capture data of musicians performing musical scores so that procedures can be developed to target variation related to individual-specific movement characteristics or coordination changes arising from movement retraining interventions.

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Appendix A

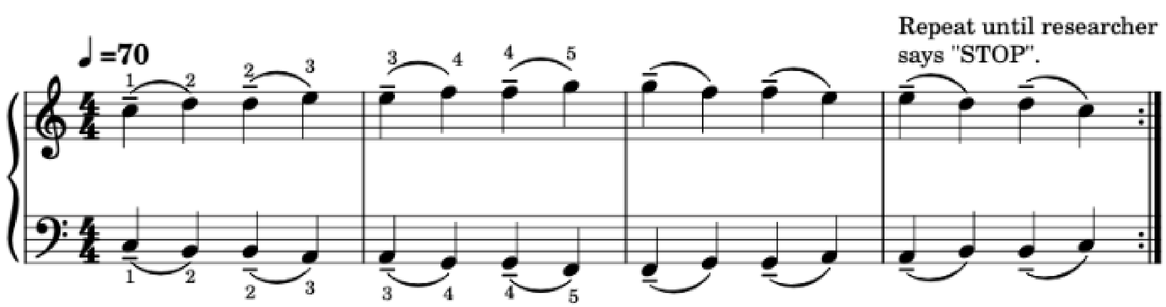
Task 1-Two Note Slurs

Description: A five-note sequence played by the right and left hand in contrary motion. Adjacent pairs of notes are connected smoothly, *legato,* and the pianist allows the keys to lift completely at the end of each connected pair, leaving a short gap in the sound.

Task difficulty: Very easy. Experienced pianists can play this task with no prior preparation.

Performance instructions: Play the task repeatedly until asked to stop (7 to 8 repetitions). Participant chooses the tempo (approximately 70 beats per minute). Play without the musical score.

Source: Task was composed for the study and is based on a common melodic gesture.



Task 2-Symmetric Fifths

Description: A sequence of blocked/harmonic 5ths played by the right and left hands symmetrically. Each 5th is played with the first and fifth finger (thumb and pinky). The 5ths are played detached (non- legato).

Task Difficulty: Difficult. This task poses a sight-reading challenge due to the frequent use of accidentals (sharps and flats) and the changing direction of the notes. Most pianists would have to practice this task to perform confidently.

Performance Instructions: Play the task repeatedly until asked to stop (7 to 8 repetitions). Participant chooses the tempo (approximately 120 beats per minute). Play with the musical score.

Source: *Mikrokosmos, Volume 2, Exercise 17b, pp. 43. Béla Bartók* (1987/1940).

Bartók, B. (1987). Mikrokosmos Volume II [Musical score]. Hawkes & Son (London) Ltd. (Original work published 1940)

Task 3-Alberti Bass

Description: Pianists play four bars with an alternating note pattern playing in the left hand while the right hand plays blocked chords. The following four measures reverses the pattern, with the right hand playing an alternating note pattern while the left hand plays blocked chords.

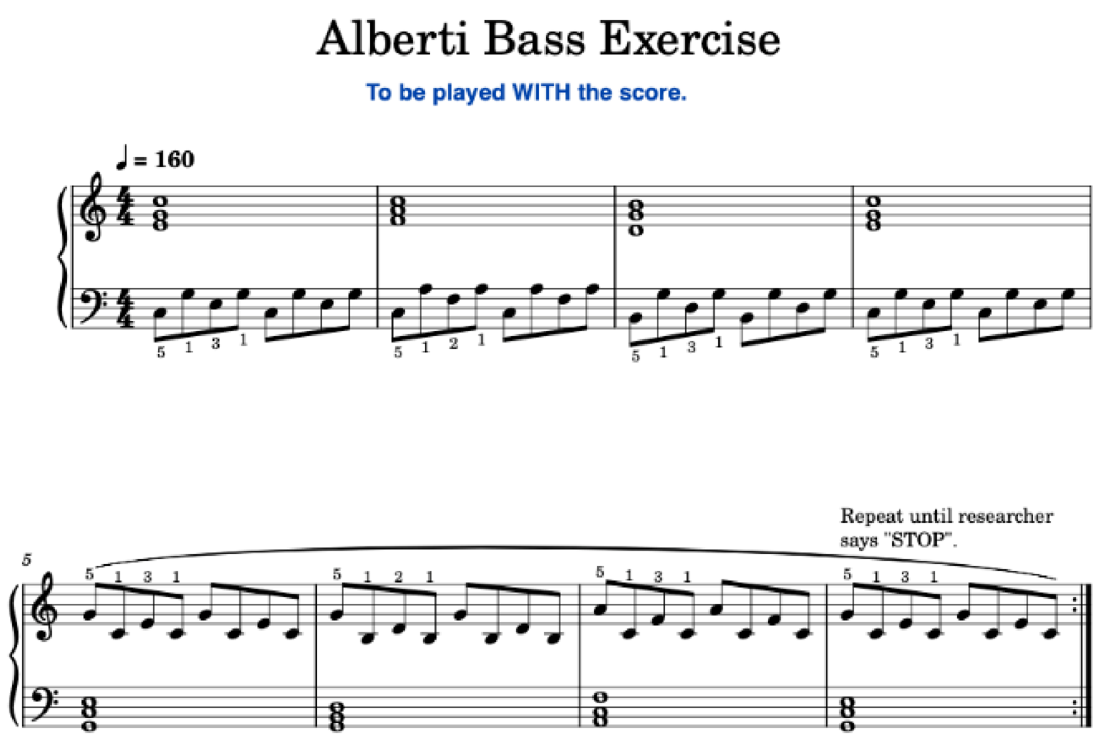
Task Difficulty: Intermediate. The Alberti Bass pattern of alternating notes is familiar to experienced pianists and highly automated from years of practice. The changing roles of the hands from bars 4 to 5 requires focus for smooth execution.

Performance Instructions: Play the task repeatedly until asked to stop (7 to 8 repetitions).

Participant chooses the tempo (approximately 160 beats per minute).

Play with the musical score.

Source: Task was composed for the study and is based on a familiar Classical-era keyboard pattern.



Task 4- *Valse Mignonne, Henryck Pachulski*

Description: A romantic era keyboard waltz of intermediate level.

Task Difficulty: Intermediate. This is a simple waltz that most experienced pianists will find easy to play after some preparation. Some pianists may find the melody in the left hand challenging

Performance Instructions: Play the piece once from beginning to end, then stop. When given a signa from the researcher, begin playing the piece a second time from beginning to end. Participant chooses the tempo. Play with the musical score and use the damper pedal.

Source: *Exploring Piano Classics Book 4*. *A Masterwork Method for the Developing Pianist*, pp. 32-33. Pachulski, H. (2010). Valse Mignonne [Musical score]. In N. Bachus (Ed.), *Exploring Piano Classics Repertoire, Book 4: a Masterwork Method for the Developing Pianist* (pp. 32-33). Alfred Music. (Original work published ca. 1906)

(Work appears on the next page.)

Valse Mignonne

Play once through with the music.

Henryk Pachulski (1859-1921)

Moderato (M.M. 𝅗𝅥. = ca. 40)

2

CHAPTER 6: ARTICLE 4

A Novel Framework of Variation in Music Performance for Planning Targeted PCA as a Tool for Measuring Coordination Characteristics in Pianists

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Abstract

PCA (Principal Component Analysis) is a valuable tool for understanding variation characteristics in motion capture data that has been applied in some previous studies on pianists' movement (Buck et al., 2013; MacRitchie et al., 2013; Tits et al., 2015). However, in standard applications PCA is only useful for generating a general view of variation characteristics in the data and it is not capable of detecting small differences in pianists' movement that may relate to participant-specific coordination characteristics (Beacon, Russell & Comeau, 2023a). Our goal is to refine PCA procedures to help create analysis methods for targeting variation in the data related to pianists' unique coordination characteristics. Such an analysis tool could provide information about how pianists respond to movement retraining interventions by providing a mathematical summary of key variation features in motion capture data sets that can be tracked over repeated measurements. However, recording pianists' movement using optical based motion tracking creates large, multivariable datasets encompassing many different sources of variation. Some variation sources are free to vary based on the musical and biomechanical choices of the performer, while others are fixed by the musical and biomechanical constraints imposed by a defined musical task. Identifying specific coordination characteristics unique to certain pianists or musical tasks and tracking how they change over time in response to movement retraining requires an analytical approach that can penetrate the many competing sources of variation in the data to reveal variation specific to the performers' movement choices. It may be possible to devise mathematical solutions for targeting variation related to performers' biomechanical choices. However, before we can begin developing PCA procedures that can target variation related to pianists' unique ways of moving, we must first identify all significant sources of variation present in motion capture data of pianists and consider how they influence PCA results. To facilitate a systematic consideration of the many types of variation contributing to pianists' motion tracking data, we propose a novel 'theoretical framework of variation in music performance' which helps categorize different sources of movement variation contributing to musical performance according to whether the variation source is free to vary with the musical and biomechanical choices of the performer or remains fixed by biochemical and musical constraints defined by the musical task. We present examples comparing the MIDI (Musical Instrument Digital Interface) data of musical patterns to plots of PC waveforms from motion capture data of piano performances to illustrate how pre-existing, task-dependent patterns can dominate the PCA results, making it difficult to identify unique features related to pianists' biomechanical choices. Applying this theoretical framework in future studies could help refine procedures for applying PCA to pianists' motion capture data to enhance the interpretability of PCA results and better understand how coordination characteristics vary between and within pianists for musical tasks of varying complexity.

Keywords: Principal Component Analysis, PCA, framework of variability, movement variation, complex movement analysis, coordination characteristics, piano performance

A Novel Framework of Variation in Music Performance for Planning Targeted PCA as a Tool for Measuring Coordination Characteristics in Pianists

Jillian Beacon, Donald Russell, Gilles Comeau

6.1 Introduction

Pianists may seek out movement retraining interventions to address issues in their postures or playing techniques that may be exacerbating playing-related-pain or impacting their ability to perform their best (Mera et al., 2023; Myers, 2016). However, there is little objective research evaluating the efficacy of various interventions in terms of their ability to change pianists' habituated coordination characteristics. Existing research has used motion tracking systems to track and measure body-positions of pianists to measure instantaneous static postures (Beacon et al., 2017; Blanco-Piñeiro et al., 2015; Blanco-Piñeiro et al., 2017; Wong et al., 2023) or to understand the function of an isolated joint or joint system kinematically in the context of simple, unimanual playing movements (Furuya & Kinoshita, 2007; Furuya et al., 2011; Furuya & Soechting, 2012). However, research has not yet arrived at a reliable method of studying full-body coordination characteristics dynamically over the course of an entire performance of typical bi-manual piano music. Studying pianists' movements as they perform musical tasks that are closely related to the type of piano playing they do during daily practice is necessary understand individual performers' unique coordination characteristics and to evaluate how movement retraining interventions may influence those characteristics over time. However, the motion capture data sets of pianists playing bi-manual piano music are several orders of magnitude more complex than those required for studying a discrete unimanual playing movement or a single joint system, making analysis more difficult.

Our previous study examined if standard PCA (Principal Component Analysis) may be able to penetrate the complexity of such data sets to distinguish between piano playing movements recorded from performances of tasks of varying levels of complexity (Beacon, Russell & Comeau, 2023a). The motion tracking data obtained during this study consisted of 66 movement trajectories generated from 22 anatomical markers placed across the pianists' bodies on anatomical landmarks on the pelvis, spine, shoulders, head, and arms. The study generated commonly used PCA output values to compare (1) the number of PCs (principal components) required to explain 90% of the variance, (2) the amount of variance described by the three largest components, and (3) the number of components describing greater than 2% variance (Beacon, Russell & Comeau, 2023a). The results of this study showed that conducting standard PCA on all 66 movement trajectories generates similar results regardless of the complexity of the playing task. PCA results were also uniform for different pianists performing the same task and for each of the three trials, which were held a week apart to allow for learning and practice effects to develop. This study concluded that in the context of piano playing, applying standard PCA to all movement trajectories simultaneously generates a high-level summary of data variation characteristics related to piano playing in general. The results cannot be used to gain insight into specific coordination characteristics of individual pianists or to differentiate between coordination characteristics that may be unique to specific musical tasks. This lack of precision makes the standard PCA values unsuitable for tracking changes to coordination characteristics over time, or for evaluating the efficacy of movement retraining interventions for pianists. The present study seeks to take a deeper look at the relationships between pianists' motion capture data and PCA results by studying plots of raw movement trajectories and PC waveforms using visual inspection. This analysis will lead to a better understanding of the characteristics of the many types of variation present in the motion capture data set, and how they influence the interpretability of PCA results. The findings of this process form the basis of a novel "theoretical framework of variation in music performance" that will guide our next research steps in creating piano specific PCA procedures that can target variation in motion capture data related to pianists' unique coordination characteristics.

6.1.1 Data Complexity and Interpretability of PCA Outcomes

PCA algorithms use linear algebra to identify ranked vectors (eigenvectors) that can be used to identify dominant variation characteristics in complex data sets comprising many variables. To conduct PCA, the data must be organized into a matrix in which each column contains successive measurements of a single variable. In the case of a motion capture data set, the x, y, and z trajectories from each anatomical marker are included as a column in the matrix. The number of rows corresponds to the number of measurements of the variables. In the case of our data, the rows correspond to the measurements of each marker's position in space at the rate of 100Hz. A standard step is preparing data for PCA is to adjust each individual measured variable so that it has zero mean (that is by subtracting the mean value of all the measurements of a variable from each of the measurements). Software performs linear transformations to find the eigenvectors of the data matrix, which can be thought of as "directions" or "axes" of variance in the data set. The eigenvector of maximal variance accounts for the greatest percentage of the overall variance and is referred to as the first "principal component" (PC). *(For* *those familiar with linear algebra, the first PC is the linear combination of the data that results in maximum variance).* The PCA algorithm carries out the same process, finding subsequent PCs for all remaining dimensions in the data set, taking the eigenvector of maximal variance perpendicular to the preceding component(s) until there are as many PCs as there are variables in the data set. The process is similar to drawing successive, independent "lines of best fit" through the data set, each representing an increasingly smaller percentage of the overall variance in the data set. However, the eigenvectors are not drawn successively through three-dimensional space, but through a dimensional space equivalent to the number of variables in the matrix. In the case of the present study, there are 22 anatomical markers, each with their own x, y, and z trajectories, resulting in a matrix with a dimension of 66. The result of PCA is a ranked list of PCs, with the first PC representing the vector along which occurs the greatest percentage of the overall variation and the last PC representing the least. A detailed mathematical account of the step for performing PCA is outside of the scope of this paper, but tutorials have been well documented in existing literature (Daffertshofer et al., 2004; Federolf et al., 2014; Federolf, 2016; Forner-Cordero et al., 2005; Shlens, 2014).

When you multiply a PC (eigenvector) by its corresponding weighting coefficients (eigenvalues), you create a reconstruction of the original data based on the variation of that vector. If you were to add up all the reconstructions resulting from multiplying the PCs by their corresponding eigenvalues, you would have the original data set. PCA does not change the data at all, but merely gives the researcher another way to represent the data that highlights variation patterns that may represent key underlying dynamics in the behaviour of a complex system. The output of PCA is influenced by how the variables in the data set vary together. Each

PC, in general, contains information from every variable (matrix column) that goes into the PC. The magnitudes of the weighting coefficients for each variable dictate how much of each individual variable contributes to the PC: higher coefficients mean that the variable contributes more to the PC than lower coefficients. Therefore, individual PCs cannot be linked to a specific variable. In the case of motion tracking data, this means that although it is tempting to draw biomechanical interpretations based on similarities in the shapes of individual PCs and raw motion capture trajectories, the shapes of individual PCs cannot be directly linked to individual anatomical markers or parts of the body, but rather contain information about how the variables move together.

Further complicating biomechanical interpretation of PCs is the presence of multiple sources of variation layered in the complex data set, many of which do not directly relate to biomechanical coordination characteristics. For example, realistic pianistic tasks would include variation from both the right hand and left hand, which may be playing rhythmically and melodically distinct patterns. The pitch and rhythmic content introduce variation patterns related to the musical task, but not necessarily biomechanical characteristics. Performers may introduce variation related to their own musical interpretation of the task by altering the loudness of the notes based on their aesthetic preferences, or by manipulating the timing of certain notes for expressive effects. Unique variation characteristics related to coordination may arise as different pianists will employ different preferred strategies for recruiting the multiple degrees of freedom afforded them in the hands, arms, head, spine, and pelvis, to execute the task. The more complex the task, the greater opportunity for variation in movement approach between different pianists. Research using PCA to study musicians' movement must contend with the high degree of complexity that results when variation from defined musical patterns, unique biomechanical characteristics, and musical aesthetic choices combine in a single data set.

6.1.2 Existing Approaches for Dealing with Data Complexity in PCA with Musicians

Much of the existing research using PCA to study musicians has dealt with the problem of data complexity and multiple sources of variation by placing substantial constraints on the musical tasks to ensure that the amount of superfluous or uncontrolled variation is kept to a minimum. As a result, most research applying PCA in studies of musicians' movement have used simple repetitive musical tasks, often limiting analysis to a single anatomical marker or sub-system of joints to narrow the competing sources of variation. By constraining performing conditions, researchers limit the sources of variability contributing to variation in the data set to help ensure that the PCA results reflects variation related to the research question. For example, studies by Verrel (2013) and Gonzalez-Sanchez (2019) limited variation in cello playing by constraining the musical task to repetitions of a single cello note on an open string. The task performed by drummers in a second part of the Gonalez-Sanchez (2019) study was similarly constrained, requiring only repeated drum strokes on a single drum. In these cases, PCA analysis was restricted to joints of the arm and did not incorporate the entire body. A study by Furuya and Soechting (2012) constrained the variability of the task by limiting the pianistic task to repeated tremolo notes in one hand, once at a prescribed tempo and once as fast as possible. This ensured that only one hand contributed to the variation in the data and that variation introduced by tempo fluctuations was partially controlled by prescribing a specific metronome speed for the control tempo. By tightly constraining the musical tasks and limiting the number of variables introduced to the PCA, the researchers ensured that the variation described by the PCA would be more closely linked to variation in the coordination of targeted joints, without being obscured by the variation introduced by varied musical patterns.

In contrast to the constrained-task approach, some researchers sought to study variation in more complex musical contexts by studying pianists' movements during the performance of complete, bimanual piano pieces. For example, in a study by Tits and colleagues (2015), each pianist played a collection of complete musical pieces based on their level of ability. PCs results reflected variation from all joints of the right and left hands and wrists, since the PCA included motion trajectories from all 26 markers simultaneously. The PCA also reflected variation inherent in the musical patterns of the pieces themselves, and any variation due to musical expression that may have been introduced by the pianist, such as variations in tempo, loudness, or articulation. The variation introduced from the musical patterns was different for each of the four pianists in the study since they were permitted to choose their own repertoire. Although the richness of variation captured in this data set better reflects movement variability expected in natural piano performance compared to the simplified tasks of the previously reviewed studies, the PCs decomposed by the PCA contain variation from so many sources that they cannot be meaningfully linked to specific biomechanical or musical features. Therefore, applying PCA on a highly dimensional data set representing a performers' movements may reveal characteristic variation patterns that broadly describe principal movement trajectories characteristic of piano playing in general (Beacon, Russell & Comeau, 2023a). This approach may give some indication about how general movement characteristics differ depending on the characteristics of the musical piece being played. However, it would be impracticable to measure how specific features of movement may differ between pianists or change over time using this approach. There are simply too many sources of variation contributing to each component to be able to meaningfully link them to specific biomechanical or musical features for the purposes of tracking them in repeated trials.

A pair of studies took steps to permit the comparison of movement characteristics between different pianists using PCA by ensuring that each pianist performed the same two Preludes of Chopin (Op. 28, No.6 and No.7) (Buck et al., 2013; MacRitchie et al., 2013). The pianists were able to choose their own tempo and make their own expressive choices during performance. To enable a meaningful comparison of movement gestures across pianists, the timescales between pianists were normalized so that the PCA reflected movement variation independent of tempo and rhythmic fluctuations between performances. Visual inspection of individual principal component plots with plots of original motion capture data trajectories played a role in analyzing how certain parts of the body may lead aspects of the performers' movements. However, although it may seem intuitive to link principal components with similarly shaped motion capture trajectories, the similarity of shape between a motion capture trajectory from a certain part of the body and a principal component does not imply equivalence with the movement of that body part. As previously explained, each principal component contains information from every motion capture trajectory submitted to the PCA. The shape and magnitude of the component plots is influenced by several factors, including artefacts of the musical patterns themselves. The different sources of variation cannot be meaningfully separated through visual inspection alone, or by normalizing the timescale of the performances.

A study by Walton (2016) presents a good example of how musical constraints affect the variation in the data set and influence the results of PCA. In this study, the PCA results describing variation in the movement of two improvising performers were heavily influenced by imposing rhythmic constraints (a metered backing track) on the improvisors. Results showed that the synergistic relationships between the two improvisors' movements depending on the musical constraints. For instance, when the improvisors played with a swing rhythm backing the variation in the data set created from combining their motion trajectories was less concentrated in the larger PCs compared to when the improvisers were playing with a drone back track. This suggests that the improvisors moved more independently in the swing condition than the drone condition. For the purposes of Walton's study, traditional PCA was sufficient to demonstrate the presence of distinct coordination patterns between the two performers in the different experimental conditions since in this case coordination was defined as the degree to which the two performers' movements varied together. The precise pitch and rhythmic content of the task was not prescribed in this study but was co-created by the two performers. Therefore, the variation related to musical task parameters was the dependent variable researchers wanted to learn more about, rather than being a pre-existing pattern that might mask individual variation of the performers. Using improvised musical tasks would not be suitable for studying how specific coordination characteristics vary within and between pianists across repeated performances, or as a means of measuring changes to coordination characteristics resulting from movement retraining interventions due to the changing variation related to the musical task. Comparing how coordination characteristics evolve over time requires that the task parameters are controlled with musical scores prescribing pitch, rhythm, tempo, and dynamics, so that researchers can discover if musicians are learning new ways to move to execute familiar tasks.

This review of existing studies using PCA to study musicians' movement demonstrates that researchers have struggled to find strategies for applying PCA that allow them to study complex movements while also making convincing biomechanical interpretations of PCs. Although some elements of the methodologies and analyses presented in these studies show some latent awareness of the need to consider the impact of data complexity and multiple sources of variation on PCA, none have systematically assessed the different sources of variation contributing to their data or addressed how pre-existing patterns may be reflected in PCA outcomes. Many of the studies imply biomechanically significant interpretations of PCs without directly acknowledging that each PC contains information from every variable included in the PC.

6.2 Purpose of Study: Developing a Theoretical Framework of Variation in Music Performance

Future research on PCA with musicians would benefit from systematic identification of the multiple sources of variation contributing to music performance data, and consideration of how the various sources of variation impact the PCA. Toward this end, we propose a novel 'theoretical framework of variation in music performance' that helps categorize different sources of movement variation contributing to musical performance according to whether the variation source is free to vary with the musical and biomechanical choices of the performer or remains fixed by biomechanical and musical constraints defined by the musical task. We present examples comparing the MIDI (Musical Instrument Digital Interface) data of musical patterns to plots of PC waveforms from motion capture data of piano performances to illustrate how pre-existing, task-dependent patterns can dominate the PCA results, making it difficult to identify unique features related to pianists' biomechanical choices. Applying this theoretical framework in future studies could help researchers better structure their methodologies to enhance the interpretability of PCA of pianists' motion capture data. This may lead to a better understanding of how coordination characteristics vary between and within pianists for musical tasks of varying complexity, paving the way for future repeated measures studies examining the impact of movement retraining interventions on pianists' coordination characteristics.

6.3 Methodology

The process of developing a data-informed conceptual framework modeling the different types of variation contributing to musical performance and thereby influencing the results of PCA involved visual inspection of a repository of raw motion capture trajectories and plots of individual principal components from PCA conducted on motion capture data of pianists performing a battery of ten musical tasks. The musical tasks were chosen to be representative of a variety of contrasting bimanual coordination patterns important in piano playing technique. Many of the tasks are notated versions of common exercises, such as parallel and contrary motion scales, that often appear in standard conservatory syllabi (Royal Conservatory of Music, 2022, p.120-124). Others were borrowed from pedagogical literature, such as Béla Bartók's *Mikrokosmos Volume II* (Bartók, 1987/1940). Some of the tasks were notated to require the same movements in symmetrical and parallel motion. Others were notated so that the right and left hand exchanged their patterns, permitting the comparison of right and left hand for similar patterns. A list of all 10 tasks can be viewed in appendix A.

6.3.1 Experimental Set Up

The process for collecting the motion capture data for this study has been previously described (Beacon, Russell & Comeau, 2023a). Six advanced pianists (four males, two females, ages 24-58, mean age: 37 years) participated in three motion capture sessions over three weeks, spaced one week apart. Prior to data collection, pianists changed into shorts and a tight-fitting black athletic top. Twenty-two reflective markers were positioned on anatomical landmarks on the participants' head, shoulders, spine, hands, arms, sacrum, and pelvis (figure 6.1). The markers on the hands, arms, shoulders, and C7 were fastened directly to the skin with adhesive tape. The four head markers were fixed to a headband participants wore around their heads so that the two front head markers were positioned centered over the orbits of the skull. The spine and sacrum markers were fastened using medical tape to fix strong magnets over the specified vertebrae. The reflective markers were then attached using magnets outside of the athletic top to ensure the markers stayed centered over the intended vertebrae despite movements of the shirt during performance trials. The two pelvic markers on the bilateral posterior superior iliac spines (PSIS) were fixed using adhesive stickers on the exterior of the clothing. Table 1 presents a full list of the location of anatomical landmarks.

Table 6.1

Anatomical Landmarks for Placement of Reflective Markers

Region	Anatomical landmarks
Head	Four markers on head band: (Two anterior skull, two posterior skull)
Spinal vertebrae	C7 T3 T7 T11 L3 Sacrum
Pelvis (bilateral)	PSIS
Arms (bilateral)	Acromion Lateral epicondyle of the humerus Styloid process of the ulna Styloid process of the radius Distal aspect of the third phalanx (just proximal to the metacarpal phalangeal joint of the third digit)

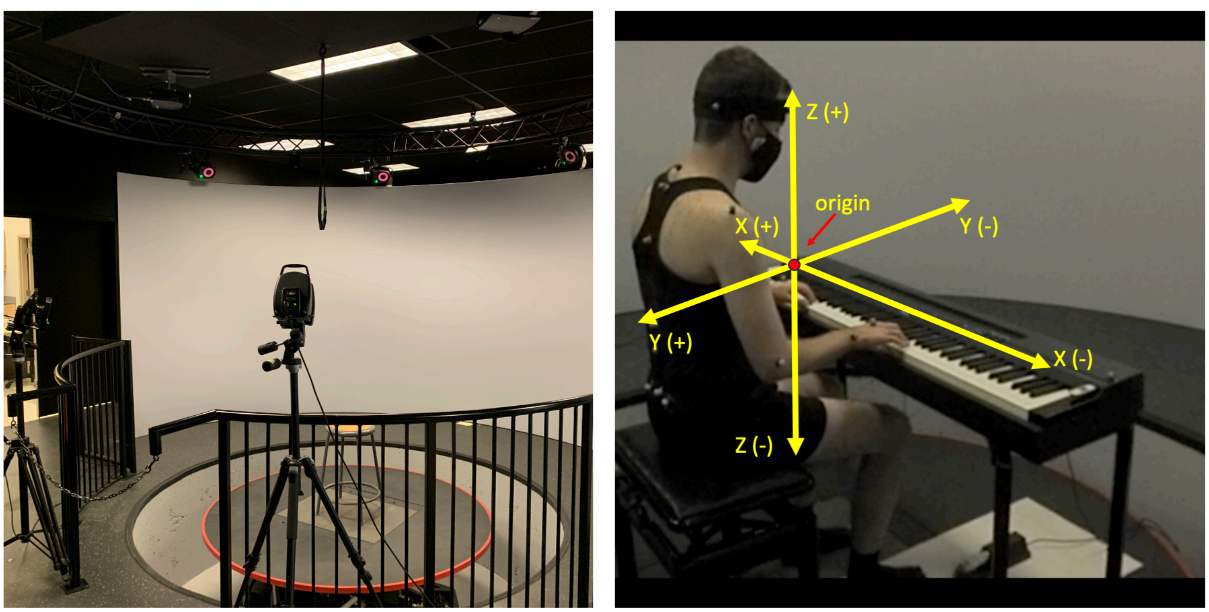
Figure 6.1

Placement of Anatomical Markers

After positioning anatomical markers, pianists warmed-up on the piano for five minutes prior to data collection. During this time participants played whatever they wished to habituate themselves to the lab environment. Many participants chose to warm up by practicing the prescribed musical tasks. 3D motion capture trajectories were collected from the 22 anatomical markers using a nine-camera Vicon system at a frequency of 100 Hz. MIDI data was collected from the Yamaha P-255 digital piano. The piano sat on a platform surrounded by a ring of seven ceiling-mounted cameras. Two cameras were placed behind the performer to ensure accuracy of tracking of the spine markers (figure 6.2). The x, y, and z axes were defined using the piano marker placed at the front left-hand corner of the instrument as the origin. The directions of the axes were defined as presented in figure 6.2.

Figure 6.2

Orientation of Vicon Cameras and Definition of X, Y, Z Axes



A reflective marker was glued to a rigid rod adhered to the lowest key on the piano. Each participant pressed this key immediately before and after each playing task. The purpose of this marker was to provide a means of syncing the timing of the MIDI data with the motion capture data. The participants performed the musical tasks at a tempo of their choosing on repeat, without pausing between the repetitions. The researcher counted seven repetitions while as the participant played. The researcher asked the participant to stop as they began the eighth repetition.

6.3.2 Musical Tasks

Pianists performed a battery of 10 technical musical tasks chosen to represent important technical piano skills. Pianists also performed *Valse Mignonne* by Henryk Pachulski (2010/1906). The results presented in this study were chosen from a subset of four musical tasks from the battery. The musical notation and playing instruction for these tasks can be found in appendix A.

6.4 Analysis

MATLAB™ was used to create a custom code to analyze the measured data. The time basis for the MIDI and motion capture data was synchronized to the motion capture time base. The MIDI time values were adjusted based on the time difference between the MIDI event corresponding to the first depression of MIDI note 21 and the first time the z coordinate of the syncing marker exceeded half the distance between its highest and lowest values.

A pattern matching algorithm matched the measured MIDI events with the events required by the musical task. As well as identifying repeated notes, missing notes and note errors, this algorithm provided the onset time of the first occurrence of the first note of the MIDI pattern and the onset time of the last occurrence of the last note of the MIDI pattern. The data files were then trimmed to include only the data between these two times.

The data was rotated to align the x-axis of the data file with the best fit line between the stationary markers on the right and left front edges of the piano and the origin of the frame of reference was shifted to the average position of the marker on the left front edge of the piano.

3D graphs were generated showing the three-dimensional locations of all the markers, as well as figures showing the individual coordinates of each marker. The data plots were organized in four functional groups containing closely related marker sets: the head marker set contains the four markers on the head, the torso marker set contains the eight markers on the spine and pelvis, the right arm marker set and the left arm marker set each contained the five markers positioned on each arm including the acromion marker. We chose these groupings because the arms and torso were expected to exhibit some independent movement characteristics based on the parameters of the selected musical tasks. Additional figures display the MIDI note values as they change over time. In these figures the MIDI notes were separated into parts (e.g., left hand and right hand) based on pitch and, where applicable, separated by note duration. Statistical summaries of the MIDI data, including note velocity (loudness), note duration (time from note onset to note offset), and inter-onset interval (time between subsequent note onsets in the same part), were computed.

Finally, the MATLAB™ code performed a PCA on four different functional sub-groupings of anatomical markers: *All* variables (including all markers); 2) *Torso* variables (including the head, spine, and pelvic markers); 3) *Right Arm* variables, including the right acromion; and 4) *Left Arm* variables, including the left acromion. The data were centered (each variable adjusted to have zero mean) but not normalized prior for performing the PC decomposition calculations. The data was not filtered since the investigation aimed to identify and categorize different sources of variation existing in the data to develop a framework that could be used in future research seeking to isolate variation related to performers' unique movement choices. Filtering the data would make premature judgements about the potential sources and meaning of variation in the data. The waveforms of PCs accounting for 2% or more of the overall variance for each were included in the figures for each different PCA.

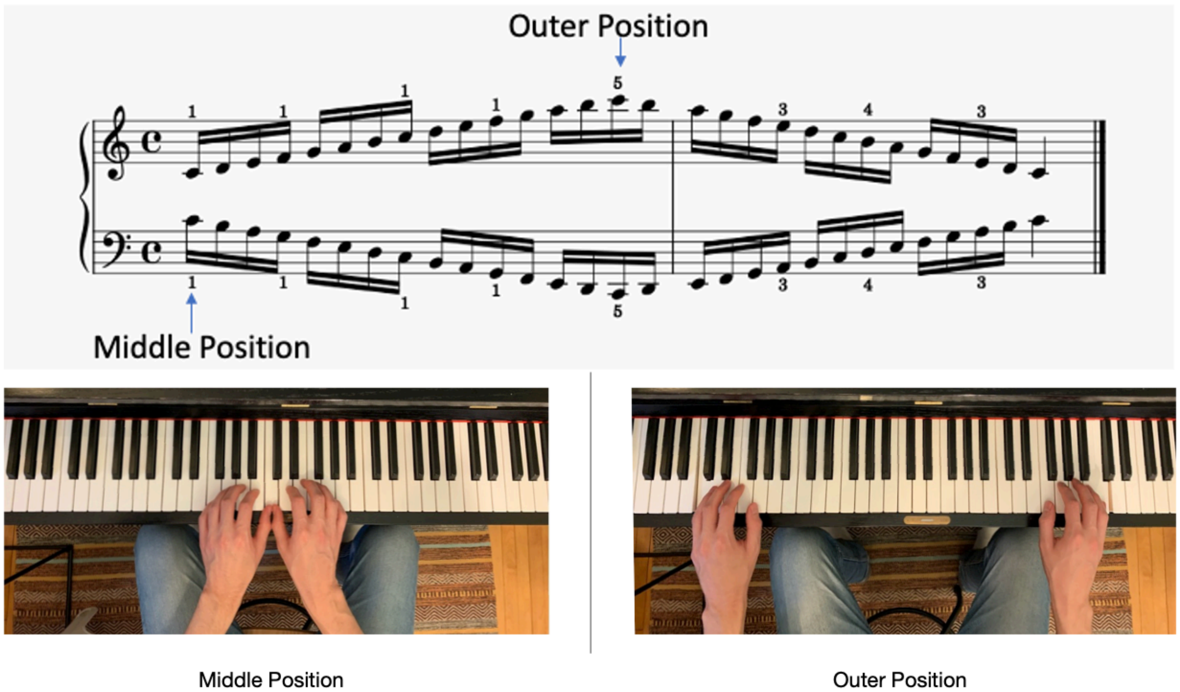
Visual inspection of the raw PC waveforms proceeded systematically task-by-task for each participant across the three trials. The primary researcher began by first looking at MIDI plots to identify note or rhythmic errors and then relating two-dimensional plots of the raw motion capture data in the x, y, and z axes and plots of all motion capture trajectories simultaneously in three dimensions. Next, the primary researcher examined the principal components accounting for two percent or greater variance and recorded observations about how distinctive PCs might be present in various groups and how PC features may relate to features in the raw data. The shapes of the raw motion trajectories were compared with features of the MIDI plots representing the tasks to visually identify movement patterns that aligned with the task requirements based on known features of the task, such as the number of the number of overall task repetitions, the number of repetitions of musical sub-units, or the number of key presses. The researcher recorded observations suggesting asymmetrical movement patterns between the right and left hand for the musical tasks with symmetrical and parallel musical structure. They also noted examples of functional subgroupings of markers exhibiting coordinated movement (varying together) or moving independently. Observations from the raw movement trajectories and MIDI plots were then compared to PC waveforms (plots of the PC vectors). In addition to conducting PCA on all the motion trajectories simultaneously, PCA was also conducted on subsets of the motion capture data based on groupings that displayed a degree of functional independence, including: 1) the left arm only; 2) the right arm only; and 3) the torso. The arm groupings included all the arm markers, and the torso grouping included all head, torso and pelvic markers (table 1). This approach was motivated by a desire to determine if task-related patterns were more strongly associated with different subsets of markers and to look for PC waveforms that may be unique to specific subsets. These forms of evidence could be used to make inferences about how different musical and biomechanical features influence the shape of PC waveforms and could help identify pianist-specific coordination characteristics. For instance, the motion trajectories of the right and left arm were compared for symmetrical tasks. Where differences were suspected, the PC waveforms were inspected to see if contrasting PC shapes existed that might arise due to different biomechanical strategies of the two arms. Observations of task-related patterns and pianist-specific patterns were considered in terms of their relationships to different sources of variation that could be contributing to the data. The findings from this visual assessment process were reviewed and used to inform the creation of a 'Theoretical Framework of Variation in Music Performance'. The visual observations were not used to make quantitative conclusions about the MIDI, position, or PC data, but were instrumental in informing the structure of the resulting model. The examples presented in the results section represent important observations from the analysis that illustrate the principles used to create this framework, providing examples of task-related variation, task-independent variation, variation related to functional groupings of anatomical markers, and random variation arising from systemic factors. The final framework appears at the end of the results section.

6.5 Results

To better understand the presence of multiple sources of variation layered in the motion capture data of performing pianists, we can consider how the data might be expected to vary for a familiar, bimanual piano playing task in which the two hands move symmetrically. An appropriate example would be a contrary-motion C major scale, depicted in figure 6.3. As a pianist performs the depicted scale pattern, they must execute a series of arm and finger movements to play the specific series of sequential notes simultaneously in the right and left hands. The inter-onset time interval of each pair of aligned right and left-hand notes in the sequence should be consistent to ensure a rhythmically smooth performance. The order of specific pitches and the regularity of the note timing are constraints that all pianists must follow for successful execution of the task. Each pianist must begin with their hands in the middle position depicted below (thumbs sharing the middle C key) and play each white key sequentially outward until their fifth fingers (pinky) arrive at the outer position in the photo on the right. Then, the pianist must return to the middle position by playing all the white keys sequentially inward. Most trained pianists will have learned a standard fingering to execute this pattern which they have likely repeated since the earliest days of study on the instrument, meaning that even the precise finger sequencing is likely to be consistent between different pianists. The pitch and rhythmic content of the task, combined with the spatial constraints imposed by the standard size and layout of the piano keyboard, and the anatomical consistency between different pianists (assuming they have two fully functioning arms and a full set of fingers on each hand) contribute pre-existing, task dependent constraints on how the anatomical markers placed on different landmarks might vary together, or move independently.

Figure 6.3

Keyboard Position and Notation of a C Major Contrary Motion Scale with Standard Fingering



Note. Although these photos depict positions for a two-octave contrary motion C major scale, the participants in the study performed three-octave contrary motion scales. Only two octaves are notated here to avoid clef changes mid-scale which may obscure the symmetric nature of the exercise for those who are not familiar with music notation.

6.5.1 Task-Dependent Variation in PCA

A large amount of the variation in the motion tracking data will reflect the parameters of the musical pattern. For example, figures 6.4, 6.5, and 6.6 depicts the raw x, y, and z motion capture trajectories from markers on spine, pelvis, and right and left arms of a participant 4 performing 3- octave contrary motion scale continuously for seven repetitions during their second-week trial. A repeated cycle at the frequency of the repetition of the task can be noted in most of the trajectories (the beginning of each repetition is marked with a red vertical line). The repeating pattern is most pronounced for the trajectories from the markers at the distal end of the arm, including the knuckles, distal radius, and distal ulna since the hands are traveling the furthest. A similar pattern occurring at the frequency of the task repetitions is also apparent in the upper spine markers (C7, T3, T7). Although the range of motion is much smaller, the repeating pattern is also observed in the acromion, lower spine markers (T11, L3) and the pelvic markers (RPSIS, LSPIS, and Sacrum). These results show that the movement trajectories of most of the anatomical markers vary together, coordinated by the constraints of the task that require the arms to travel out and back in repeatedly throughout the exercise.

Figure 6.4

Raw X, Y, Z, Motion Trajectories of Torso Markers of 3-Octave Contrary Motion Scales Performed by Participant 4, Trial 2

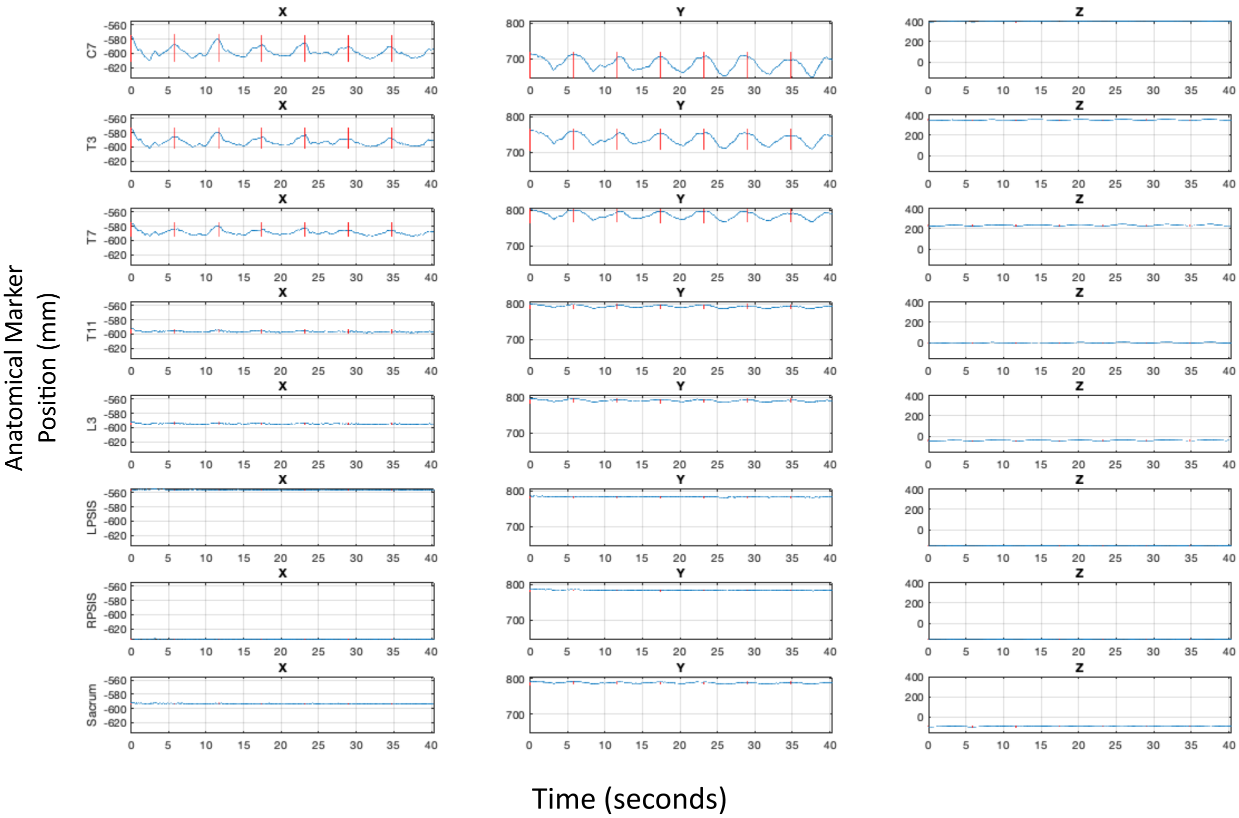


Figure 6.5

Raw X, Y, Z, Motion Trajectories of Right Arm Markers of 3-Octave Contrary Motion Scales Performed by Participant 4, Trial 2

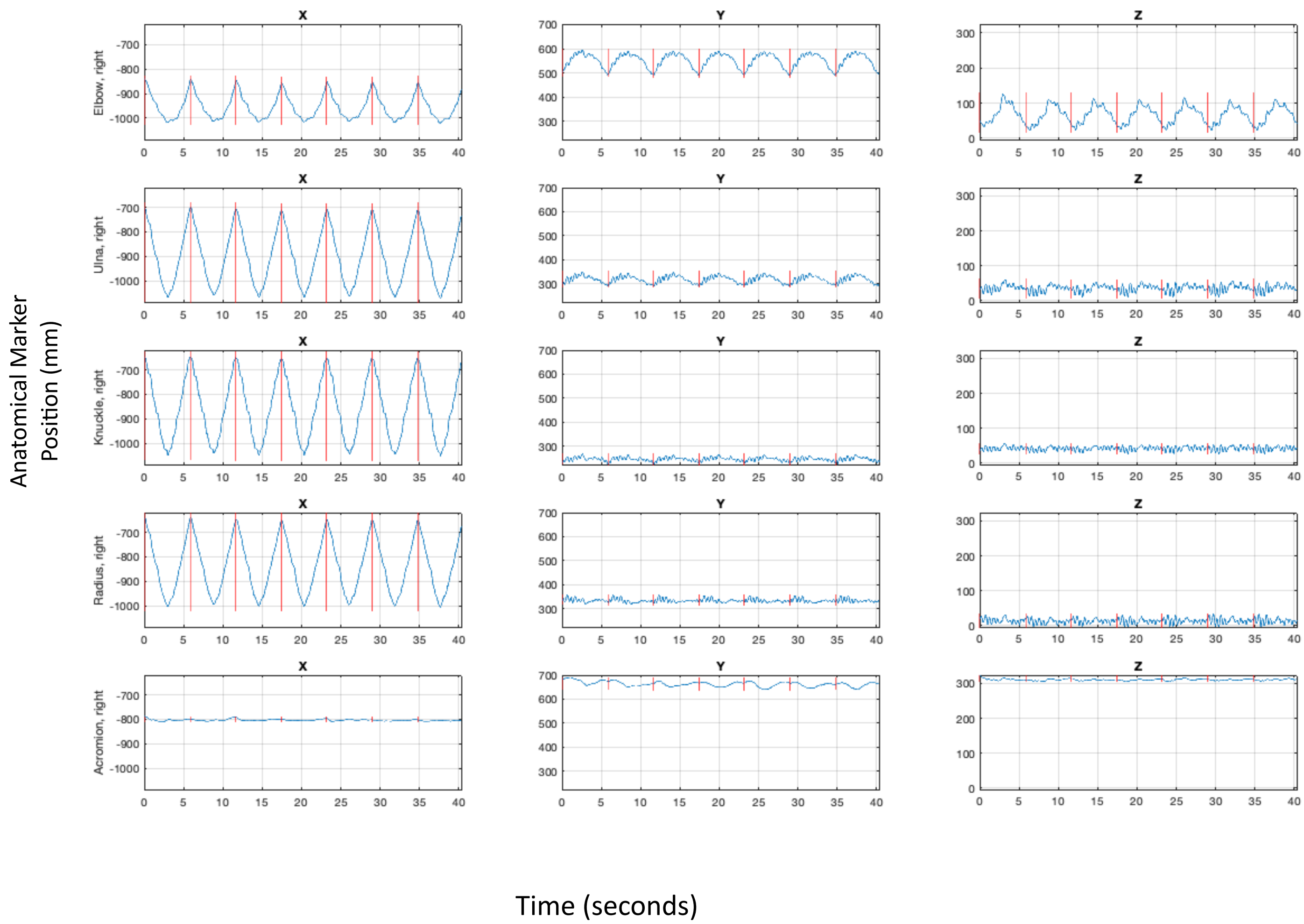
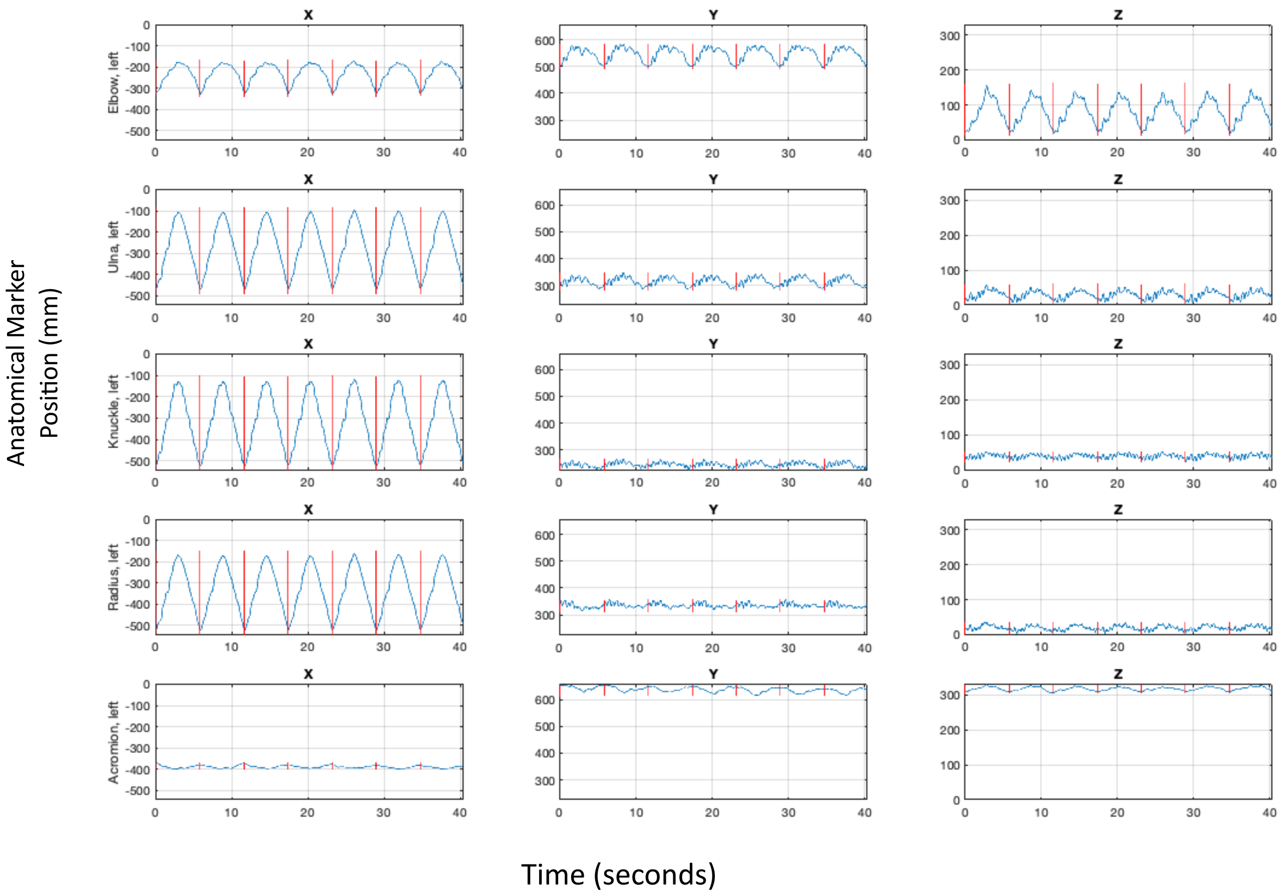


Figure 6.6

Raw X, Y, Z, Motion Trajectories of Left Arm Markers of 3-Octave Contrary Motion Scales Performed by Participant 4, Trial 2

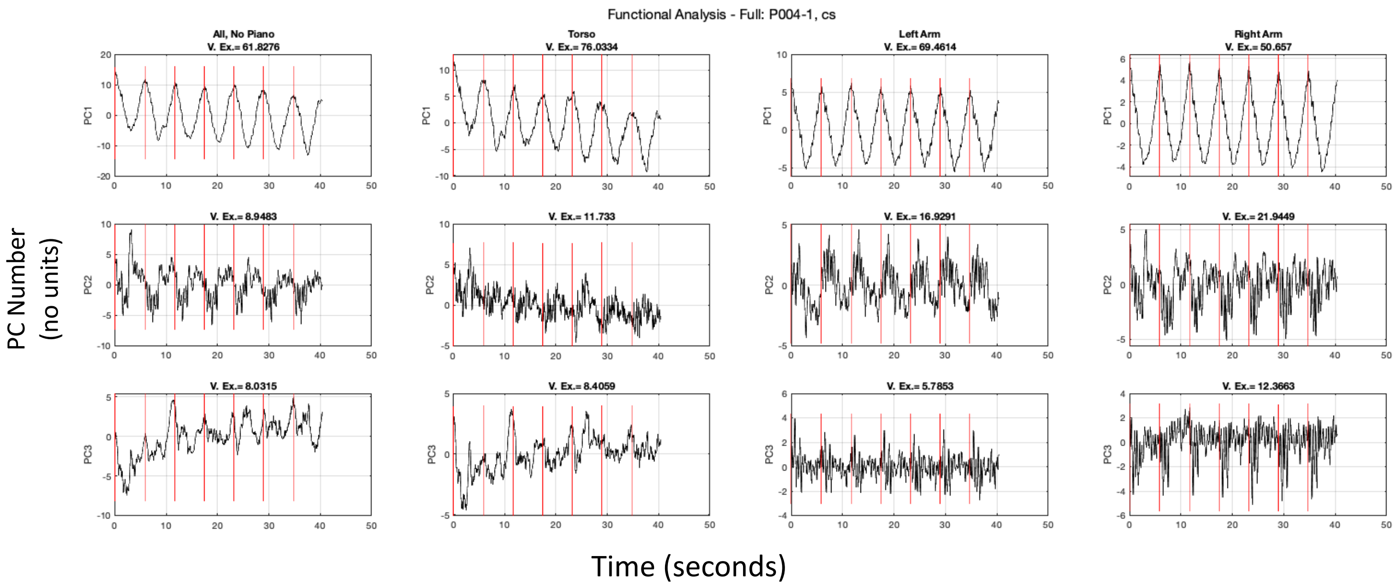


Since all the markers move together to execute the task parameters, it is not surprising that plots of the first PCs appear to have the same shape and frequency characteristics as the raw motion trajectories when PCA is run on motion trajectories of all the markers. The pattern is also seen in PC1 when PCA is done on only the torso markers (spine, pelvis, and head), only the left arm markers (including the left acromion) and only the right arm markers (including the right acromion). This can be viewed in the top row of PC plots below in figure 6.7. This example shows that the variation pattern related to the similar movement of the anatomical markers as they execute the task parameters accounts for the largest proportion of overall variance in the PCAs conducted on the functional subgroupings: 1) 62% for all markers; 2) 76% for the torso markers; 3) 69% for the left arm markers; and 4) 51% for the right arm markers (rounded to the nearest whole number). The relationship of the shape of the first component to the task parameters suggest that the majority of variance in the data is driven by the spatial layout of the task on the keyboard. No matter which participant or trial is examined, PC1 retains the same characteristics. Therefore, the variation explained by this first component mostly describes something about the variation inherent in the task itself. The information about how the pitches vary are defined by the musical score at the outset and is therefore known and can be defined ahead of time. PC1 does not provide meaningful information about unique variation characteristics the pianist may be exhibiting but does suggest that most of the markers coordinate across the body to execute task parameters.

The second and third rows of figure 6.7 displays the second and third PCs of the marker subgroups, respectively. Variation occurring at the frequency of the task repetitions is also seen for PC2s, which account for less of the overall variance. The higher frequencies observed in PC2 and PC3 correspond to the frequency of the individual keypresses in the exercise. The key-pressing frequency represents another source of variation that is inherent to the task but does not contain meaningful information about unique coordination characteristics of individuals, since it is expected to be there based on the parameters set out for the task and can be defined at the outset. Together, the note-pressing frequency and the patterns repeating at the frequency of the task repetitions dominate the shapes of most of the PC waveforms illustrated in figure 6.7.

Figure 6.7

PC Waveforms of the First Three PCs of PCAs conducted on Functional Subgroupings Based on the Marker Trajectories of 3-Octave Contrary Motion Scales Performed by Participant 4, Trial 2



Note. The vertical red lines mark the beginning of each new repetition of the task.

A second example illustrating the dominance of task-determined variance can be seen in the Symmetric 5ths task (Bartók, 1987/1940), notated below in figure 6.8. The MIDI note diagram derived from participant 1’s second trial appears below the task notation (figure 6.9).

Figure 6.8

Symmetric 5ths Task Derived from Bartók's Mikrokosmos, Volume II, No. 17b

Figure 6.9

MIDI Notation of Symmetric 5ths Task from Participant 1, Trial 2

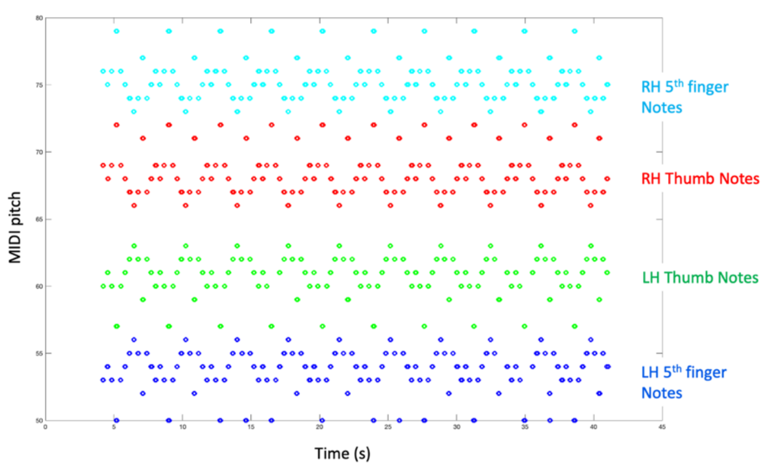


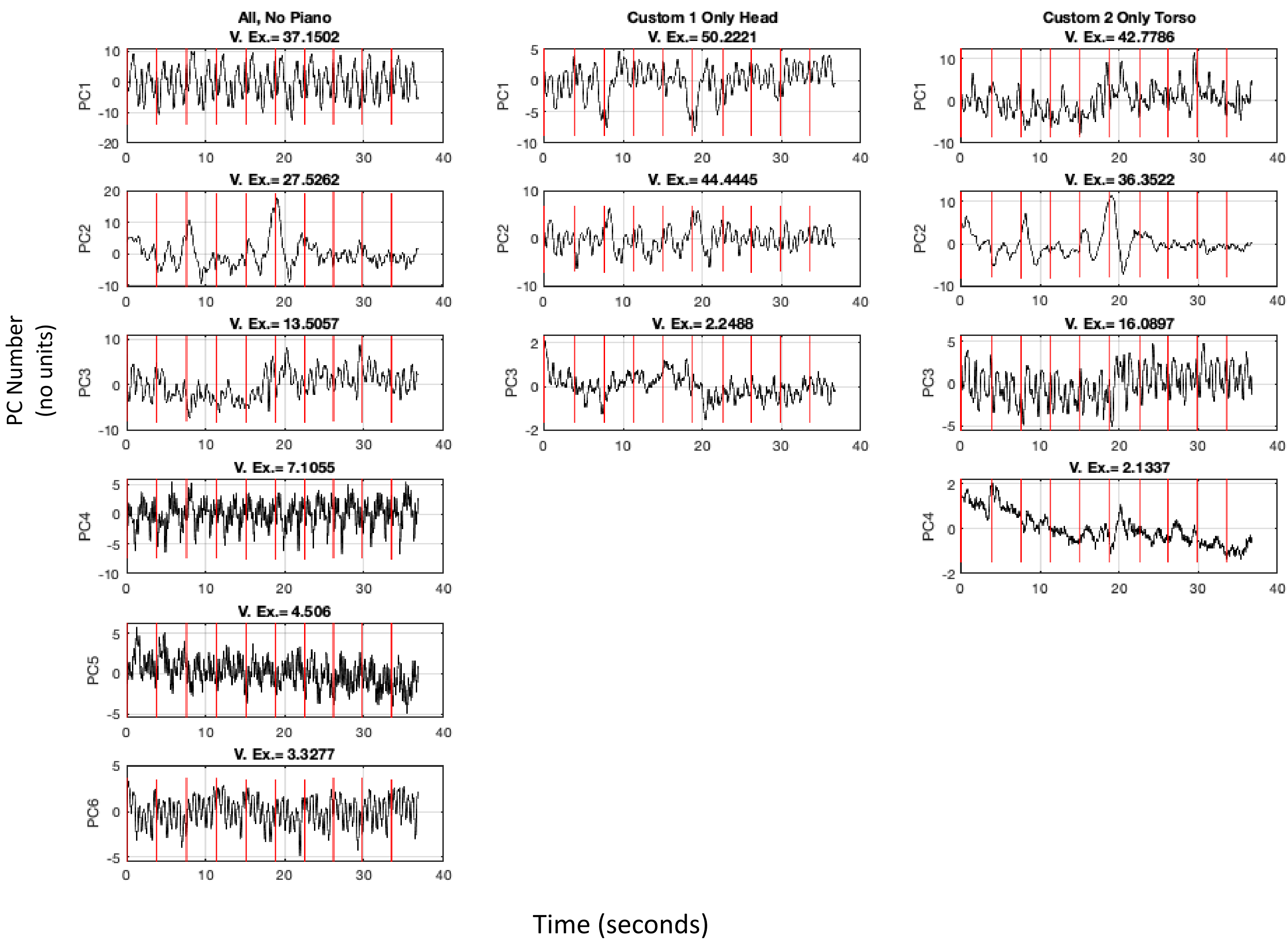
Figure 6.10, A) and 6.10, B) displays the PC waveforms of the functional sub-groupings of the markers for PCA of all markers, head only, torso only, right arm only, and left arm only. Many of the waveforms exhibit repeating patterns related to the frequency of the task repetition, especially in the case of the right and left arm, but also for some of the earlier PCs for the head and torso. Higher frequencies occur at the frequency of chord playing, and at a higher frequency of unknown origin. Upon inspection of the corresponding raw movement trajectories (figure 6.11), it appears that the higher frequencies could be related to repetitive

movements of the wrist and knuckles in the y (forward and back) and z (vertical) planes that may be part of the pianists' biomechanical strategy for striking the thumb and fifth finger notes simultaneously and pushing off the keys to move toward the next location on the keyboard. As was the case in the contrary motion scale, the x-axis trajectories of the arms appear to be most closely related to the variation of the task itself, based on the similarity of the shapes of the x-trajectories with the MIDI plots, and with the shape of PC1, especially for the arms and all marker PCAs. However, the presence of many layered sources of variation related to the task characteristics makes it difficult to separate biomechanically relevant variation from variation related to task parameters.

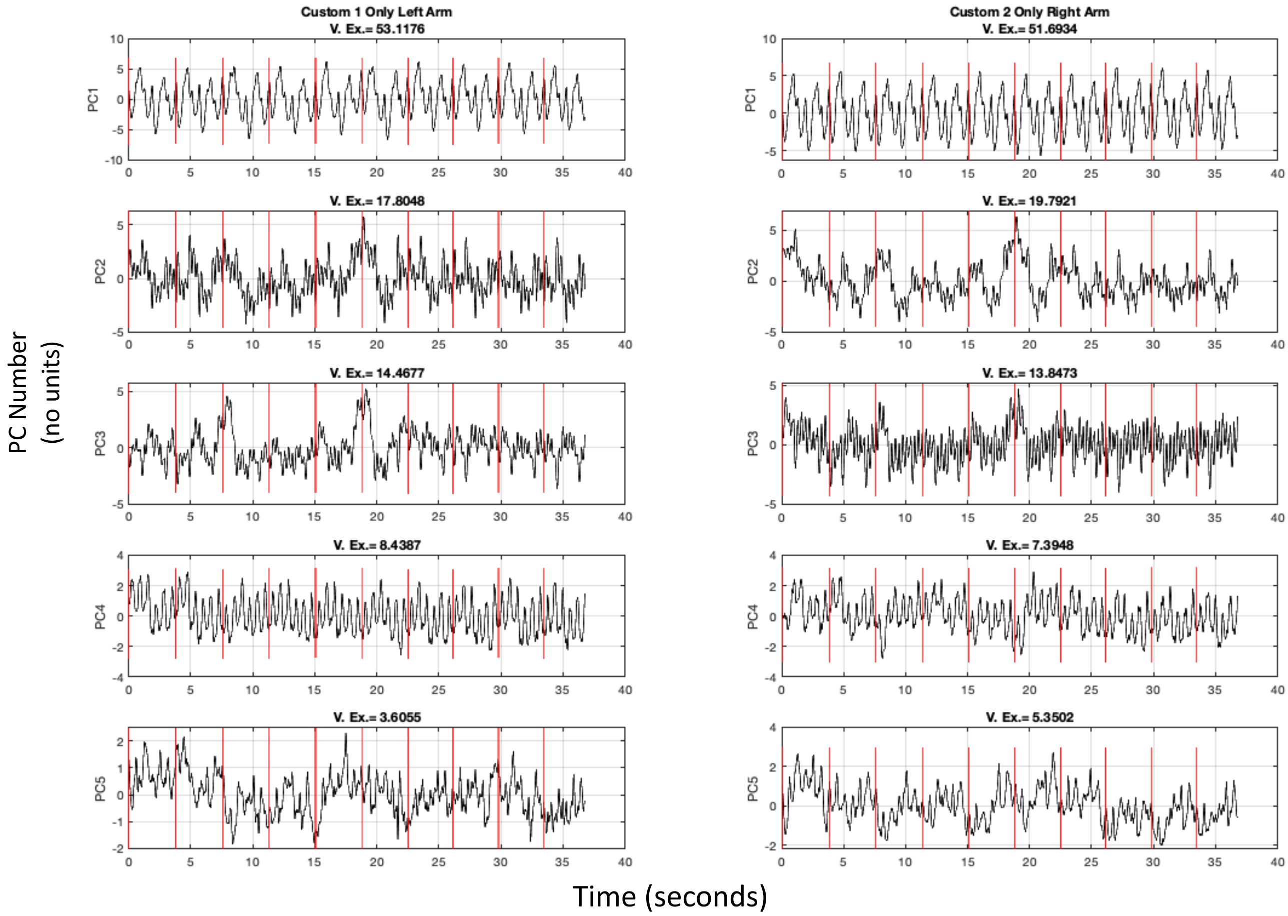
Figure 6.10

PC Waveforms from PCA on Functional Groupings: All, Head, Torso, Right Arm and Left Arm for Symmetric 5ths, Participant 1, Trial 2

A) Head and Torso



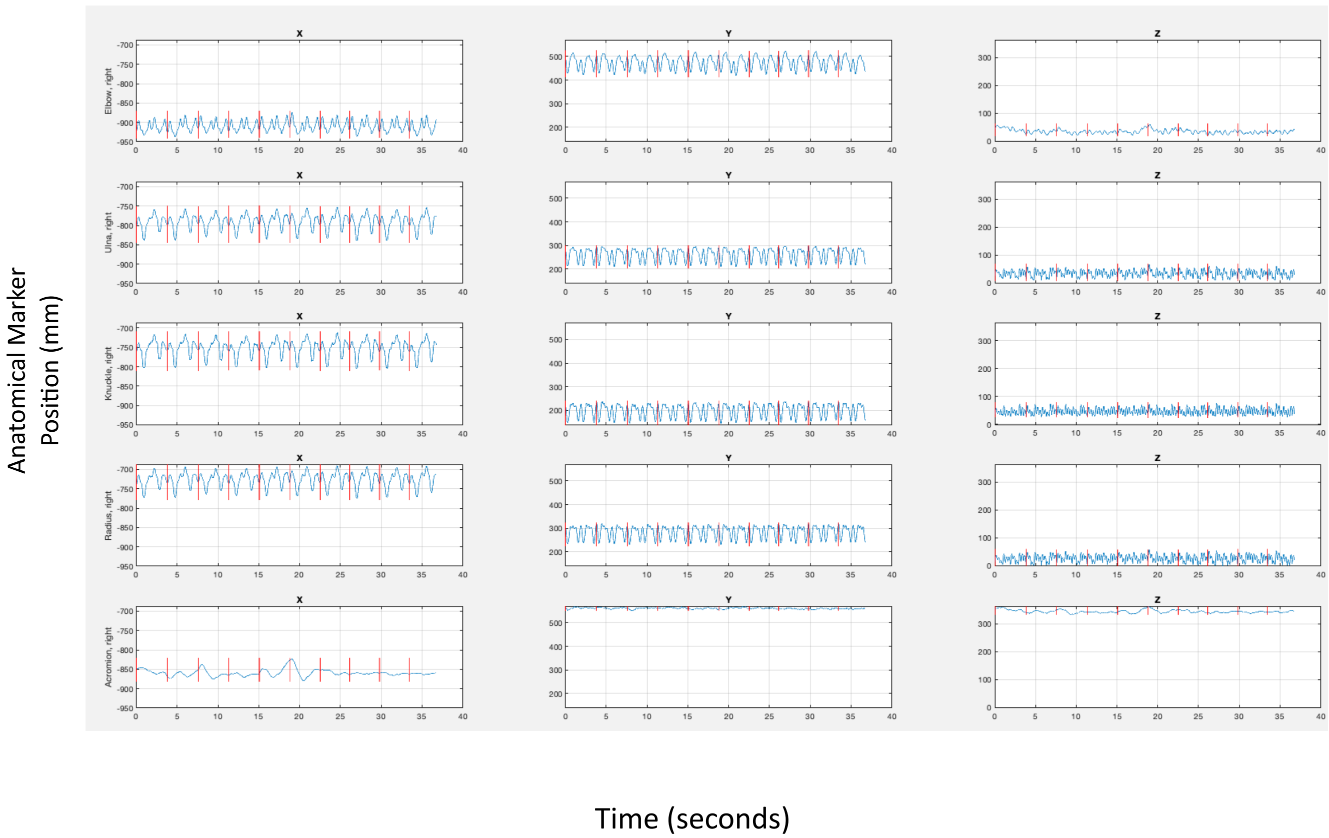
B) Left and Right Arms



Note. Figure A) displays PC wave forms for all markers (left column), the head markers (middle column) and the torso markers (right column). Figure B) displays PC wave forms for the left arm markers (left column) and the right arm markers (right column).

Figure 6.11

X, Y, and Z Trajectory Plots of Right Arm Markers of Participant 1, Trial 2 Playing Symmetric 5ths



Note. Left column contains x trajectories, middle column contains y trajectories, and right column contains z trajectories.

6.5.1.1 Conclusions About the Impact of Task-Dependent Variation on PCA.

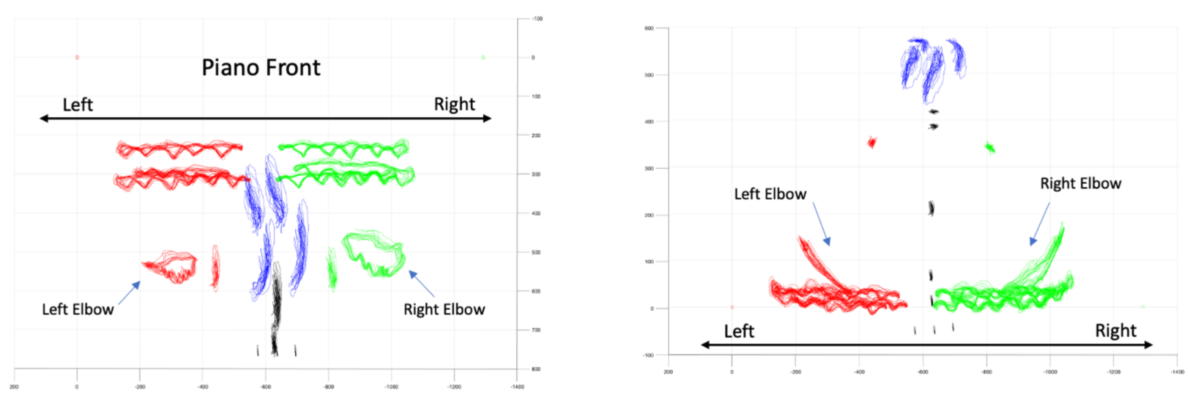
The preceding examples are representative of some features that were consistently observed when examining the raw motion trajectories and PC waveforms of different tasks performed by different pianists. In most cases, the first or second PCs accounting for the largest amount of overall variance in the data set could be clearly linked by shape and frequency content to variation features of the task, represented by MIDI plots. Furthermore, it was common to find frequencies in the PC waveforms related to the frequency of note-presses appearing the both the complete PCA of all markers, and the PCA of the right and left arm subgroupings. These relationships were clearly observable by counting associating the number of peaks in the repeated patterns in the PCs at different time scales and relating them to the known number of task repetitions, the number musical sub-unit repetitions, and the number of individual keypresses. These task-dependent patterns seemed to be dominant in the larger PCs, but often appeared in many of the smaller PCs accounting for less variance. This suggests that variation relating to musical patterns is highly dominant in the PCA. The variance related to the parameters of the musical task are known *a priori* and would be consistent for all pianists performing the same task. Therefore, the dominance of this type of variance in the data may be obscuring the ability to detect pianist-specific coordination characteristics in the PCA results.

6.5.2 *Variation That is Independent of Task Parameters in PCA*

During the analysis, it became apparent that sometimes movement characteristics varied due to participants' unique coordination characteristics and the differences could not be attributed to differences in the musical patterns. Due to tightly constrained task parameters, many aspects of the raw motion trajectories will appear similar for a given task across different pianists. However, pianists can employ different movement strategies flexibly to execute the same task, resulting in different coordination characteristics between pianists. For instance, symmetrical tasks such as the previously described contrary-motion scale (figure 6.3) provide good bases for exploring variation that is task independent because the task constraints are musically and biomechanically symmetrical for the right and left hand. Even though parameters of the playing task are musically and biomechanically symmetrical, some pianists may exhibit different trajectory characteristics between the right and left arm. This phenomenon could arise for many potential reasons, such as a difference in dexterity between the right and left hand. Alternatively, the pianist may consciously attend to one hand more than the other, resulting in one hand 'leading' the motion, while the other hand follows more automatically. For instance, the right and left arm of participant 1 exhibit some different movement characteristics during the performance of the symmetrical three-octave contrary motion C-major scales during trial one. The 2D top view and back view of all marker trajectories in figure 6.12 show that the elbow movements stand out from the other trajectories as asymmetrical, primarily in the y-x plane (front and back, and right to left). Examination of individual raw trajectory plots confirmed this observation, which is evident in the different range of motion and pattern shape in the Y-axis trajectory plots from the right and left elbow markers (figure 6.13).

Figure 6.12

Top View and Back View of Motion Trajectory Plots for Participant 1's Performance of Contrary Motion Scales, Trial 1 (mm.)



a) Top View b) Back View

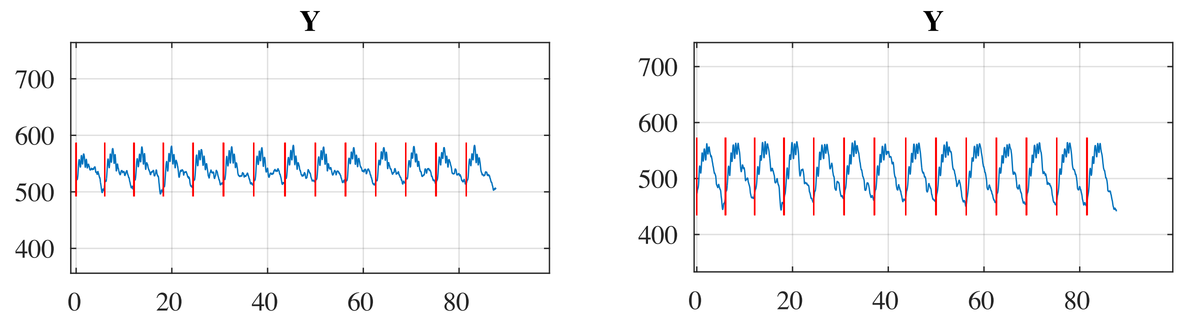
Note. Blue trajectories correspond to head markers. Black trajectories correspond to spine and pelvic markers. Green markers correspond to the right arm and shoulder markers. Red markers correspond to the left arm and shoulder markers.

Figure 6.13

Y-axis Trajectories of the Right and Left Elbow Markers for Participant 1's Performance of Contrary Motion Scales, Trial 1 (mm.)

Left Elbow, Y-Axis

Right Elbow, Y-Axis

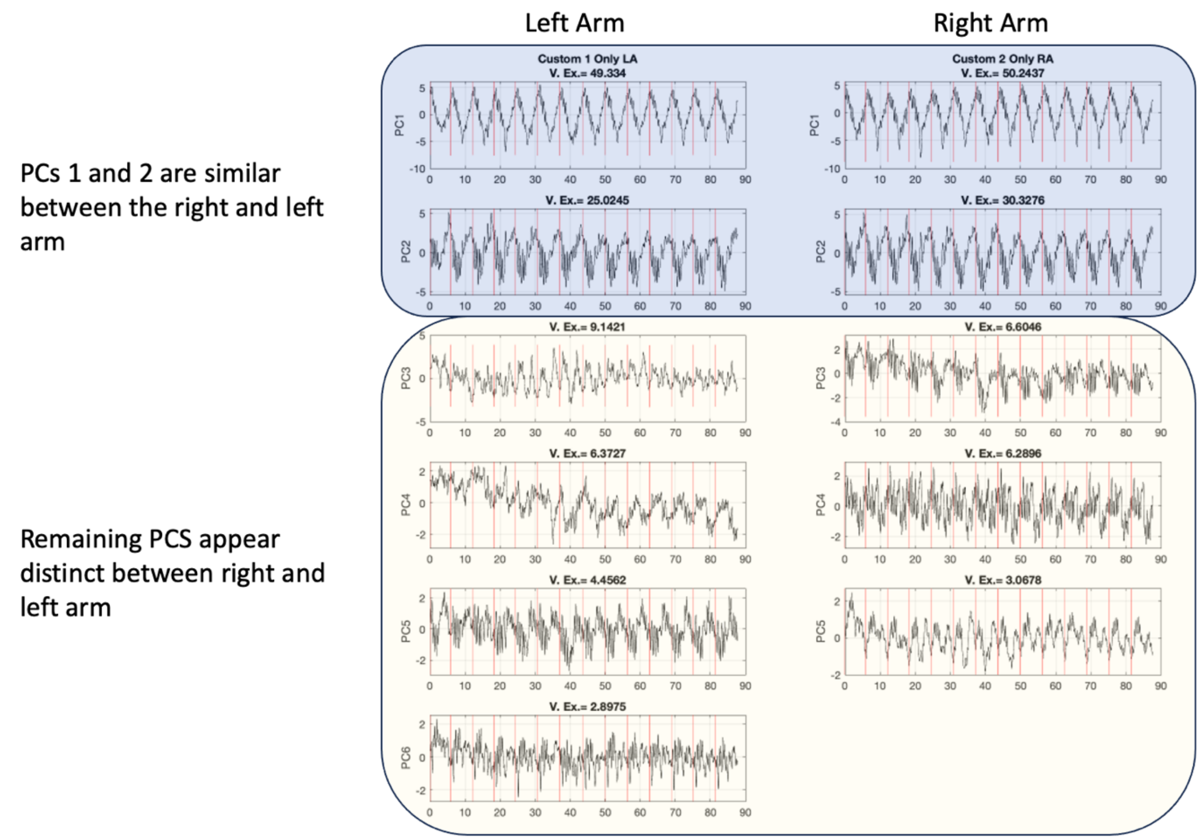


Time (seconds)

Studying the PC waveforms from the left and right arm PCA in figure 6.14 (the middle and right column, respectively) shows that although PC1 and PC2 seem very similar for the left and right arm, the shapes of PCs 3 through 5 are more unique, and do not visually correspond in terms of larger and smaller frequencies, or the macro shape of the PCs. The left arm displays one more component greater than 2% compared to the right arm, suggesting there is more variability in the movement of the left arm compared to the right. Further research could mathematically compare the similarity of the various waveforms to establish a measurement movement symmetry between the right and left arm for this symmetrical task. However, as was evident in previous examples, the most prevalent variation patterns appear to be those occurring at the frequency of the task repetition and the keypresses. With those task-defined patterns dominating the PC waveforms, it is difficult to make biomechanical interpretations of the differences viewed in the right and left PCs. Without dealing with these competing patterns, the PCs are not currently effective at quantifying characteristics of pianists' unique coordination patterns.

Figure 6.14

PC Waveforms from PCA of All Markers, the Right Arm Markers Only, and the Left Arm Markers Only

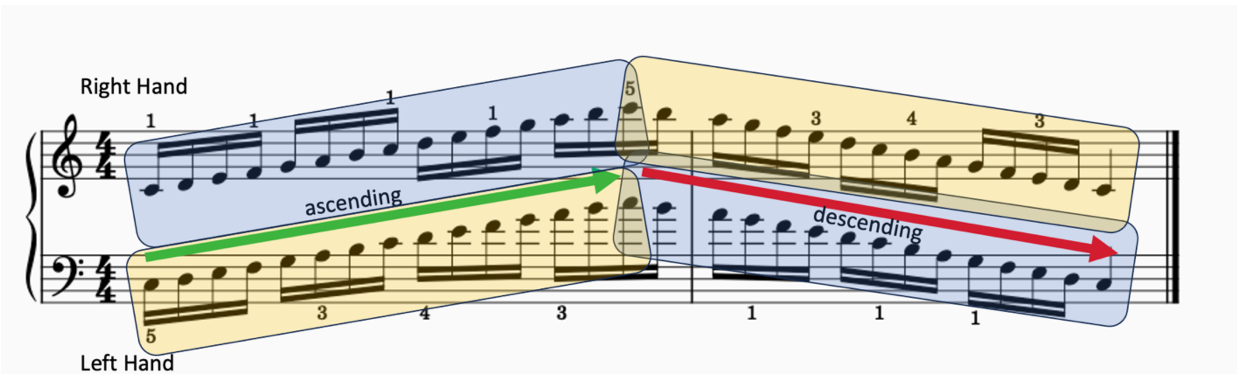


Exercises where the hands play the same musical pattern in parallel in both ascending and descending directions can also provide good bases for comparing movements in the right and left hand. In parallel tasks, such as the parallel motion C-major scale pictured in figure 6.15, the hands perform biomechanically symmetric movements, but at different phases of the task. The finger sequence the RH uses in the ascending portion of the scale is the same finger sequence the LH uses for the descending portion of the scale. Similarly, the finger sequence the

LH uses in the ascending portion of the scale is the same finger sequence the RH uses in the descending portion of the scale.

Figure 6.15

C Major Parallel Motion Scale

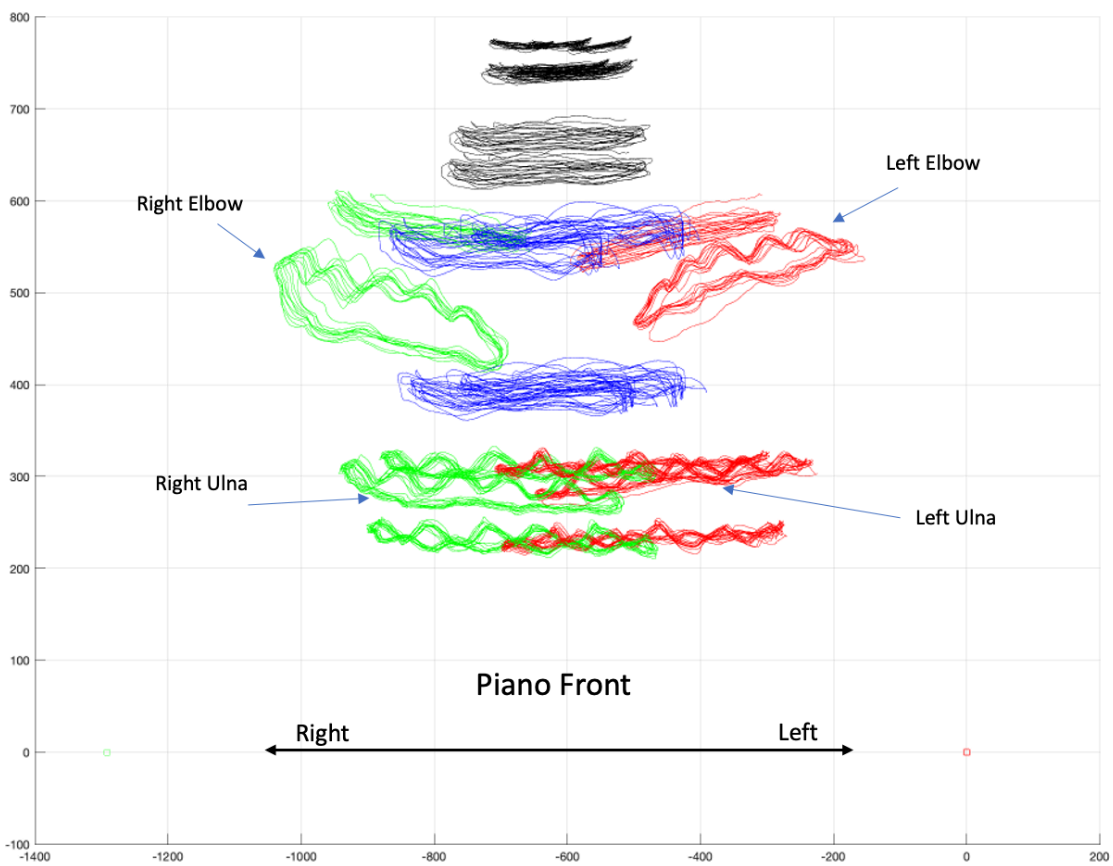


Note. Yellow corresponds to identical finger sequences starting on finger 5. Blue corresponds to identical finger sequences starting on finger 1. Participants performed this exercise in three octaves rather than two. The example notates two octaves to avoid the use of excessive ledger lines or clef changes.

If pianists were to use highly similar movements for corresponding finger sequences in the right and left hand, then theoretically the movement trajectories should look very similar for corresponding phases of the task in the right and left hand. The right and left arm PCA should also yield similar results. However, in practice pianists may deal with the cognitive demands of playing a different finger sequence in each hand simultaneously by consciously attending to one hand more than the other. This is one possibility that could lead to different movement characteristics in the right and left arm. For example, figure 6.16 shows that participant 1’s right elbow moved with a much larger range of motion than the left elbow.

Figure 6.16

Top View of Motion Trajectories for Participant 1, Trial 1, Parallel Motion Scales (mm.)



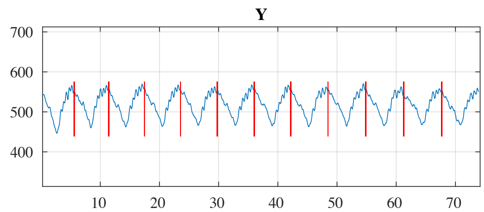
Note. Blue trajectories correspond to head markers. Black trajectories correspond to spine and pelvic markers. Green markers correspond to the right arm and shoulder markers. Red markers correspond to the left arm and shoulder markers.

When plotted individually, most of the x, y, and z marker trajectories look nearly identical between the two hands. However, plotting the individual arm-marker trajectories demonstrate that the right and left arm movements appeared slightly different in specific axes, especially for the elbow z-axis, ulna z-axis, knuckle x and y axes, and radius x and y axes (figure 6.17).

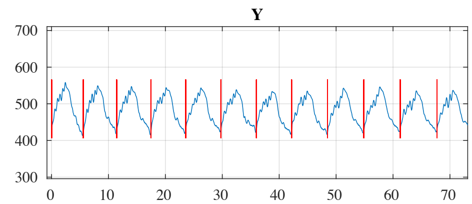
Figure 6.17

Motion Trajectories Exhibiting Differences in Movement Characteristics Between the Right and Left Arm for Participant 1's Performance of Parallel Motion Scales, Trial 1 (mm.)

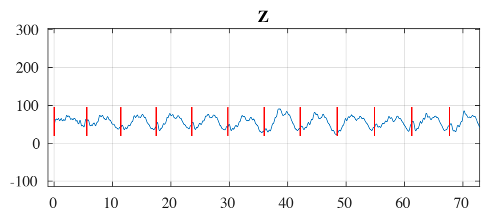
Left Elbow, Y-Axis



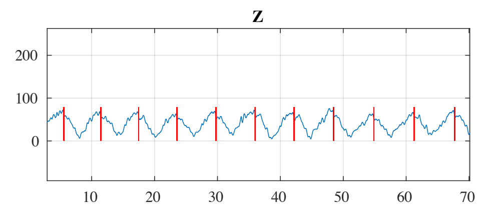
Right Elbow, Y-Axis



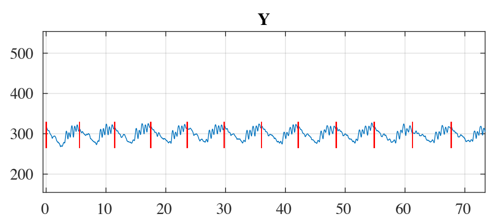
Left Elbow, Z-Axis



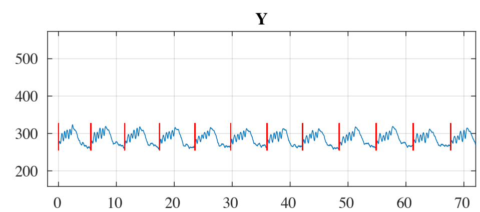
Right Elbow, Z-Axis



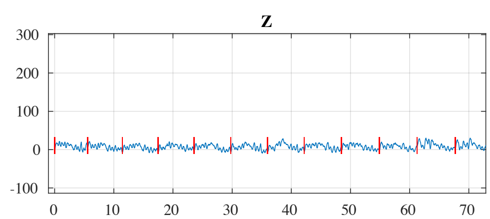
Left Ulna, Y-Axis



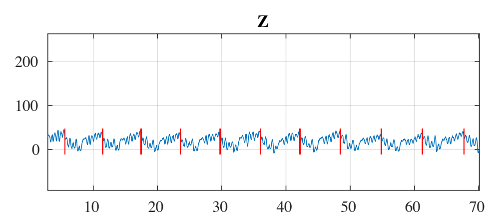
Right Ulna-Y-Axis



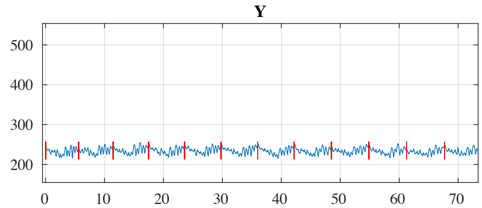
Left Ulna, Z-Axis



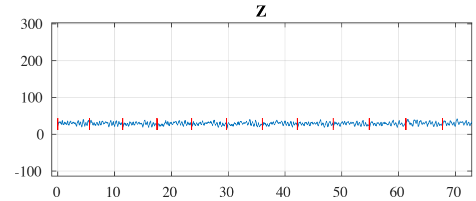
Right Ulna, Z-Axis



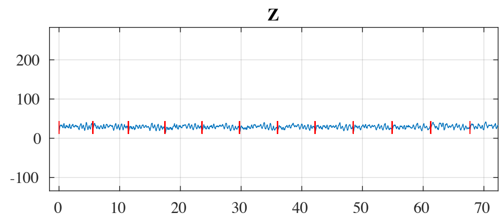
Left Knuckle, Y-Axis



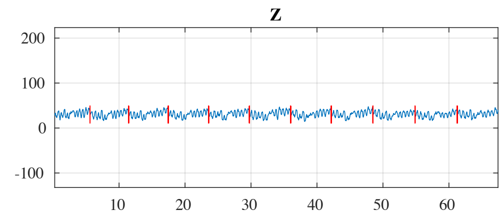
Right Knuckle, Y-Axis



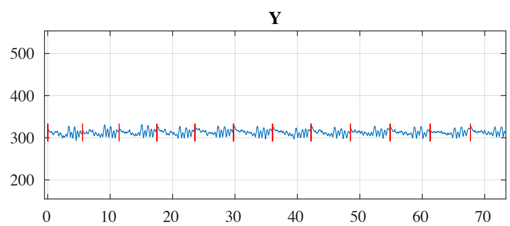
Left Knuckle, Z-Axis



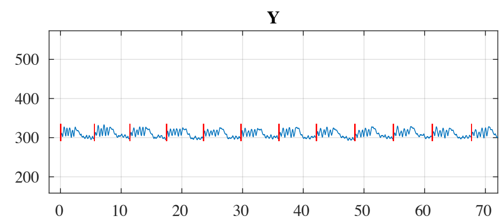
Right Knuckle, Z-Axis



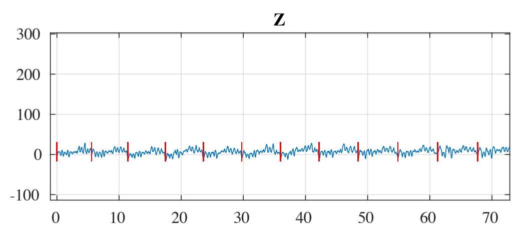
Left Radius, Y-Axis



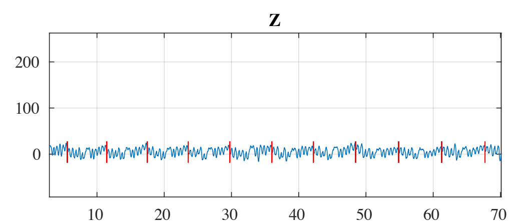
Right Radius, Y-Axis



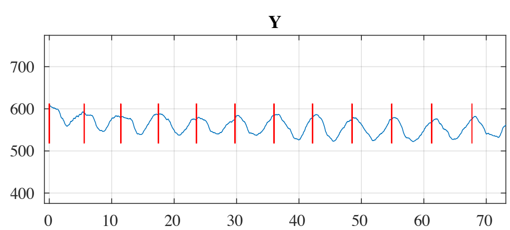
Left Radius, Z-Axis



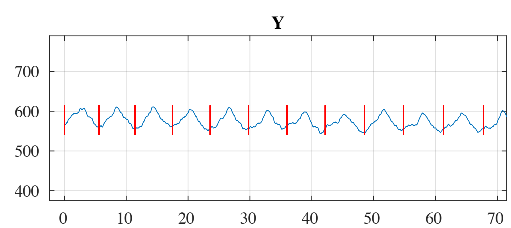
Right Radius, Z-Axis



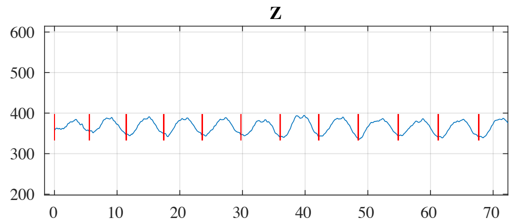
Left Acromion, Y-Axis



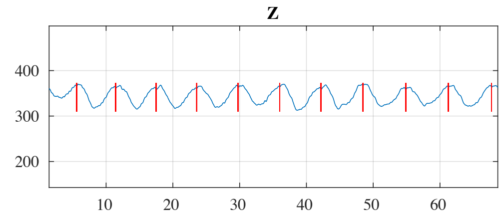
Right Acromion, Y-Axis



Left Acromion, Z-Axis



Right Acromion, Z-Axis

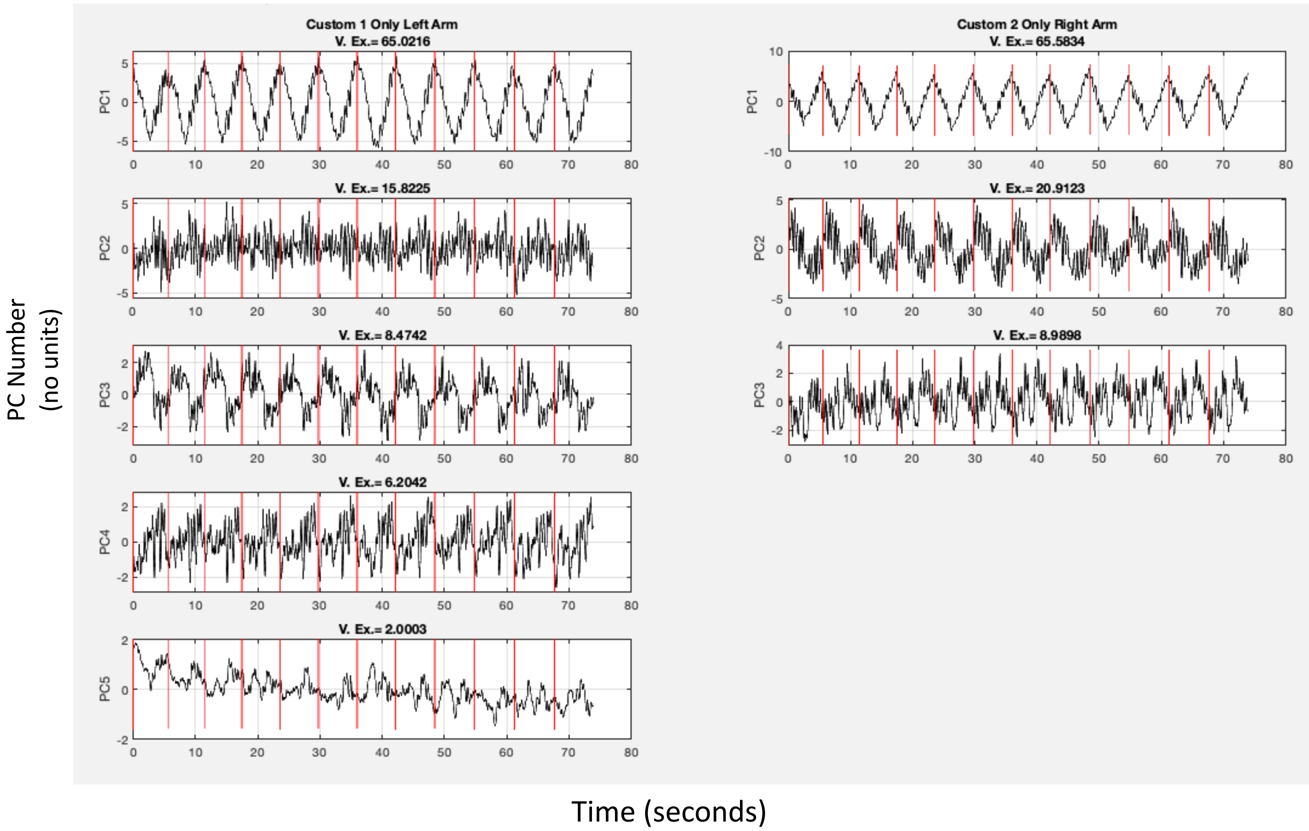


Note. Y-axis positions are measured in mm. X-axis is measured in time (seconds).

Examining the PC waveforms from the left arm and right arm independent PCAs highlights the existence of differences in the right arm and the left arm movements (figure 6.18). Aside from PC1, there are no other obviously corresponding shapes between the PCs of the right arm and the left arm. Furthermore, the left arm has two more components accounting for greater than 2% of the variance than the right arm has, suggesting the left arm has more diversity in its variation patterns. However, it is not clear from the PC waveforms how these different variation patterns relate to specific biomechanical coordination characteristics. Furthermore, each of the PC waveforms, except for PC5 of the left arm, is dominated by frequency content at the frequency of the task repetition and at higher frequencies which may be related to key-press frequencies. Ultimately, the combination of different sources of variation in the PCs mean that we are only able to tell that a difference in coordination patterns exists between the right and left arm for this task. We cannot comment with specificity about what coordination characteristics might be accounting for those differences.

Figure 6.18

PC Waveforms for the Left and Right Arm Only PCA of Participant 1's Performance of Parallel Motion C Major Scales, Trial 1



Interestingly, the differences in the right and left arm appeared to be similar for the both the contrary motion and parallel scales for this participant, as can be seen by comparing figures 6.10 and 6.14. Something about the difference in organization of the joints of the right and left arm persist for this individual whether the task is played in contrary or parallel motion. Developing new procedures for using PCA to target variation related to coordination characteristics might help elucidate the specific features of this participant-specific coordination characteristic and investigate if similar coordination features persist in other types of musical tasks for this participant.

6.5.2.1 Conclusions About the Impact of Task-Independent Variation on PCA.

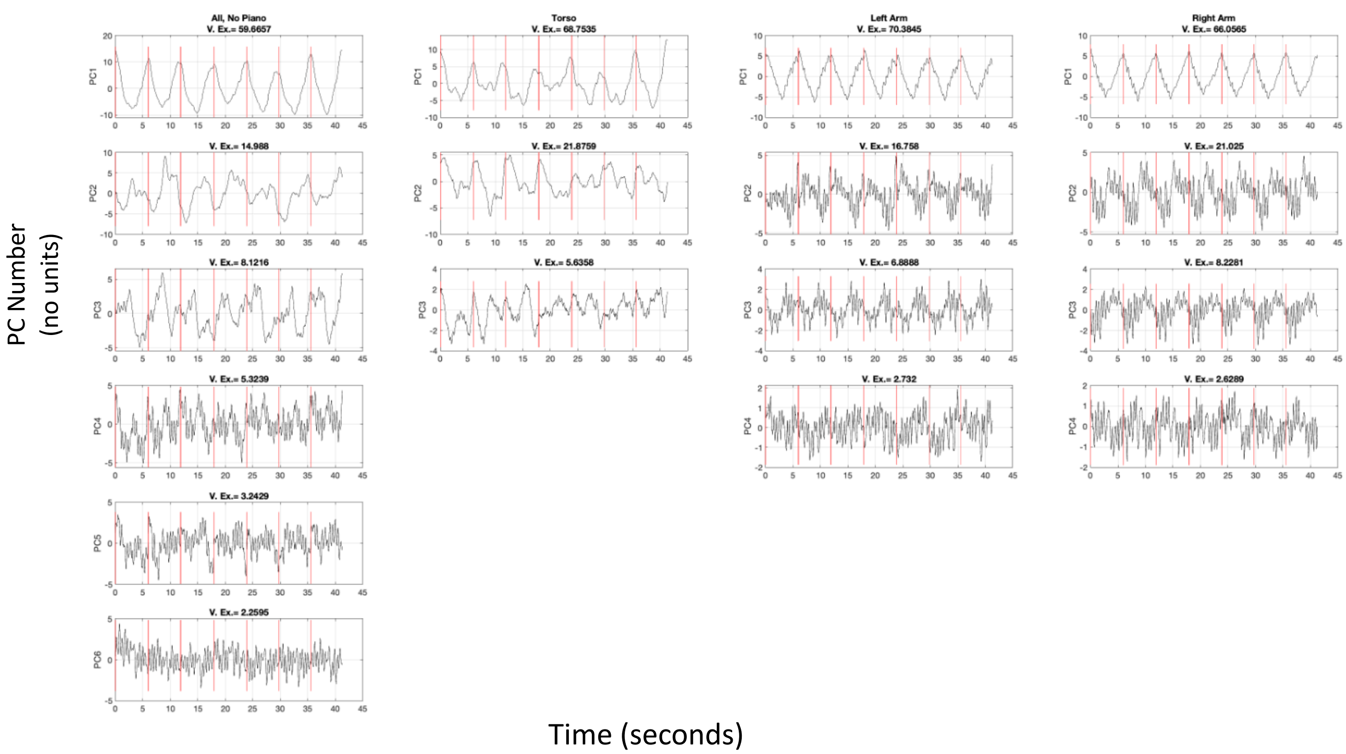
The visual analysis yielded several examples where unique variation patterns existed in the right and left arm for parallel and symmetric tasks that have identical musical and biomechanical task requirements for each hand. The distinctness of the PC waveforms between the right and left arm in these cases indicate that examining the characteristics of PC vectors could help detect the presence of different coordination characteristics in the right and left arms when they are performing the same task. However, the dominance of task-determined patterns in PC waveforms discussed in the previous section continue to obscure the subtler variation related to intra- and inter-individual coordination characteristics. This analysis suggests that using symmetric and parallel tasks might be a good place to start when experimenting with new ways to remove task-determined variation from data sets to help PCA target variation patterns related to unique coordination relationships.

6.5.3 Variation Related to Biomechanical Functional Groupings

During the analysis it became clear that often the shape and frequency content of PC waveforms generated from torso-only PCA were distinct from those of the arm-only PCA for PCs other than PC1. Typically, PC1s had similar macro shapes across the All, Torso, Left Arm, and Right Arm PCAs, with the arm PC1s often containing some higher frequency content reflecting the frequency of keypresses. However, torso PCs of numbered two or higher often displayed more erratic shapes, lower frequency content, and a lack of clear pattern occurring at the frequency of the task repetition. A clear example of this appears in the PC waveforms of participant 4's performance of parallel motion C major scales (figure 6.19). The PC waveforms of the torso do not have a clear pattern that repeats with the task repetitions, and they lack the higher frequency content present in the arm PCs reflecting the key-press frequencies. PC1 through PC3 of the 'All' PCA are clearly more strongly related to the variation patterns in the torso whereas PC4 through PC6 are more strongly related to the variation patterns in the arms. This feature may reflect the fact that for many musical tasks, the arms can move independently of the torso. Provided the arms can lengthen comfortably to reach the necessary keys, the torso and pelvis can function independently of the task, providing a base of support for the movement of the arms. As this example displays, the arms are more directly involved in executing the musical pattern than the torso. As a result, the arm-only PCs that have more in common with the musical pattern.

Figure 6.19

PC Waveforms of Participant 4's Performance of Parallel Motion C Major Scales, Trial 1

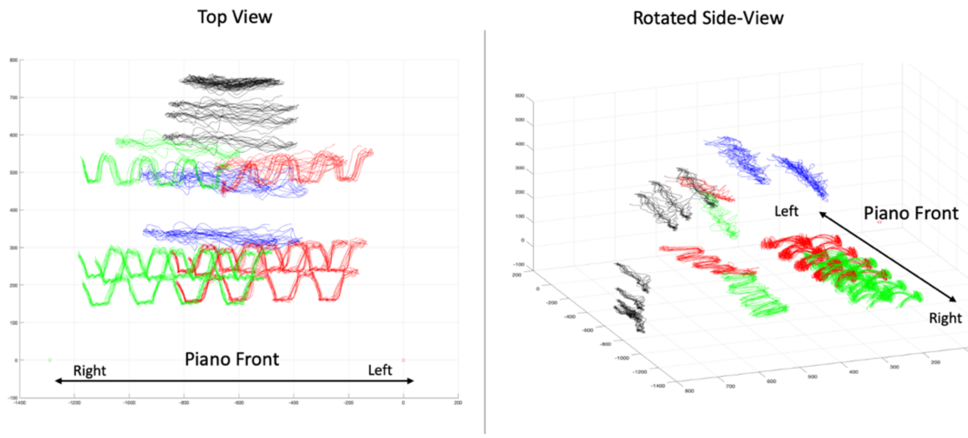


Note. The far-left column contains PC waveforms from the all-maker PCA. The middle-left column contains PC waveforms from the torso PCA. The middle-right column contains PC *waveforms from the left arm PCA. The far-right column contains PC waveforms from the right arm PCA.*

However, the analysis revealed that the organization of coordinated piano movements are not always divided along boundaries of the torso and arms. Pianists are capable of flexibly adjusting the parts of the body that are coordinated in the performance of musical tasks, depending on pianists' unique movement preferences. For example, all participants except number 4, displayed independent coordination of the torso and arms for the blocked octaves playing task, as can be seen in the example from participant 3 in figure 6.20. For this task, the hands must play three octave consecutive white keys, then move forward in the y-axis to play three consecutive black keys. The pianist alternates between three white keys and three black keys for the entire length of the keyboard, both ascending and descending, resulting in the blocked pattern seen in the hand and arm movements in figure 6.20. Most participants exhibited coordination patterns like those exhibited by participant 3, consisting of primarily x-axis movement in the head, spine, shoulders, and pelvis, as the torso moved side to side to reach the extreme ends of the keyboard. For most pianists, any torso movement forward and backward in the y-axis had a narrower range of motion and a more random variation that wasn't clearly linked to the musical pattern. As expected from the independence exhibited between the torso and the arms in the motion trajectories, the PC waveforms from the torso PCA were visibly distinct from those of the right and left arm PCAs (figure 6.21).

Figure 6.20

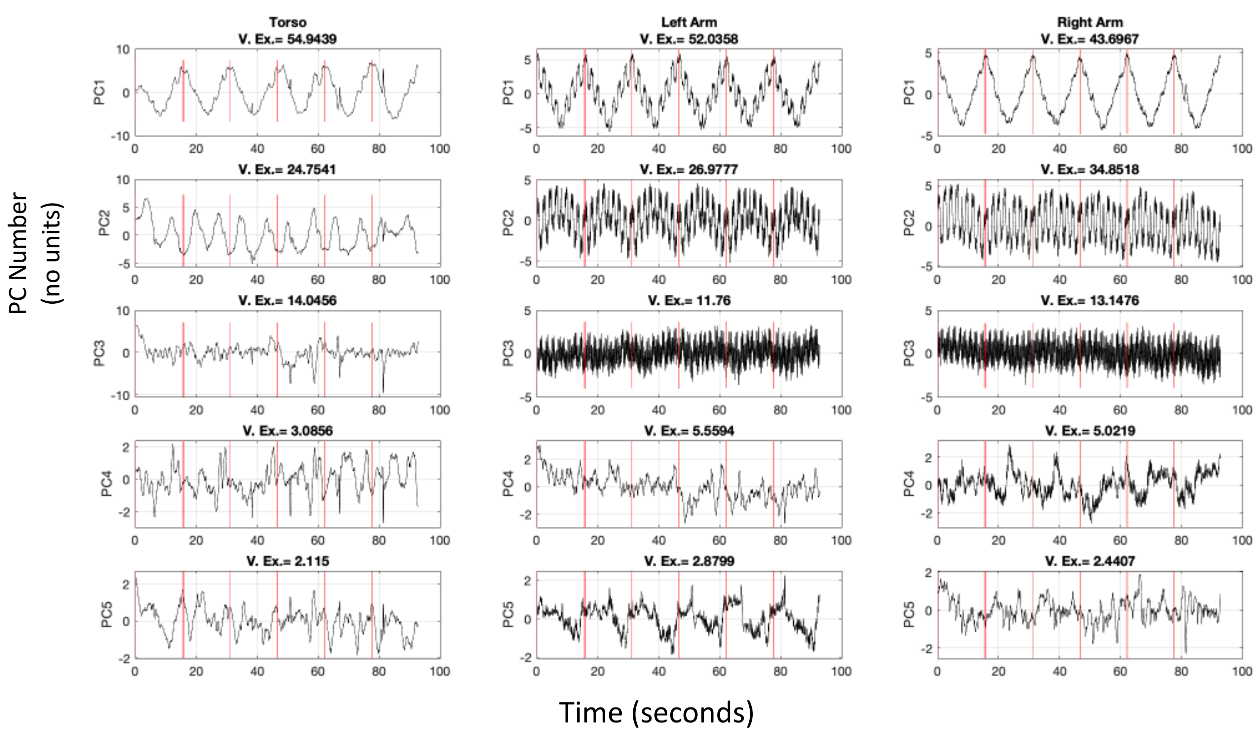
Motion Trajectory Plots for Blocked Octaves Task, Participant 3, Trial 1 (mm.)



Note. Blue trajectories correspond to head markers. Black trajectories correspond to spine and pelvic markers. Green markers correspond to the right arm and shoulder markers. Red markers correspond to the left arm and shoulder markers.

Figure 6.21

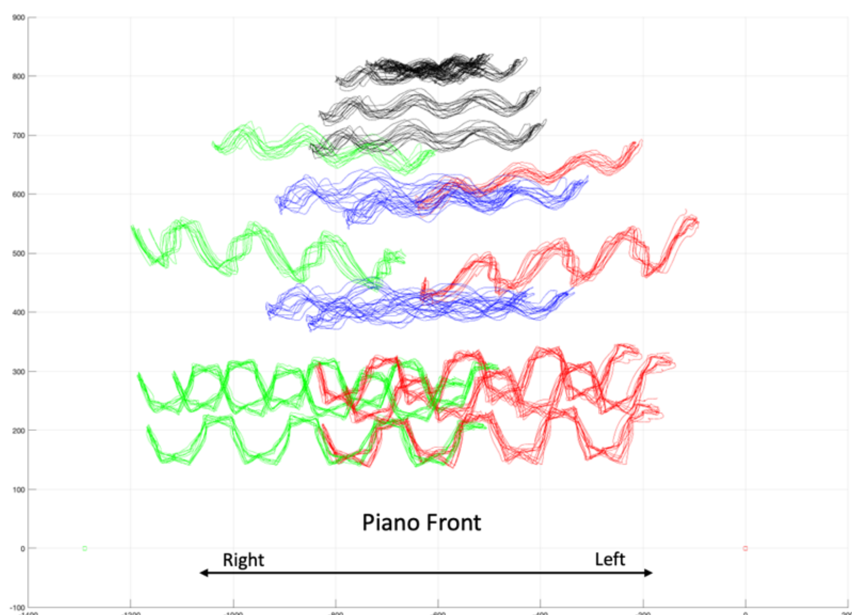
PC Waveforms from Torso, Left Arm, Right Arm PCAs for the Octave Task, Participant 3, Trial 1



Contrastingly, participant 4 exhibited a consistent coordination pattern across the entire body in the x-y plane, with the pelvis, spine, shoulders, and head coordinating in a similar pattern to the arms. Participant 4's torso and arms were coordinated, and their movement characteristics were closely related to the variation inherent in the task pattern (figure 6.22). As expected from the coordination exhibited between the torso and the arms, all PC waveforms reflected a dominant pattern at the frequency of the task repetition, and most exhibited variation at the frequency of alternation between white keys and black keys in the task (figure 6.23). The consistency of this pattern across PCs is evidence of the cross-body coordination of the markers, driven by the task characteristics.

Figure 6.22

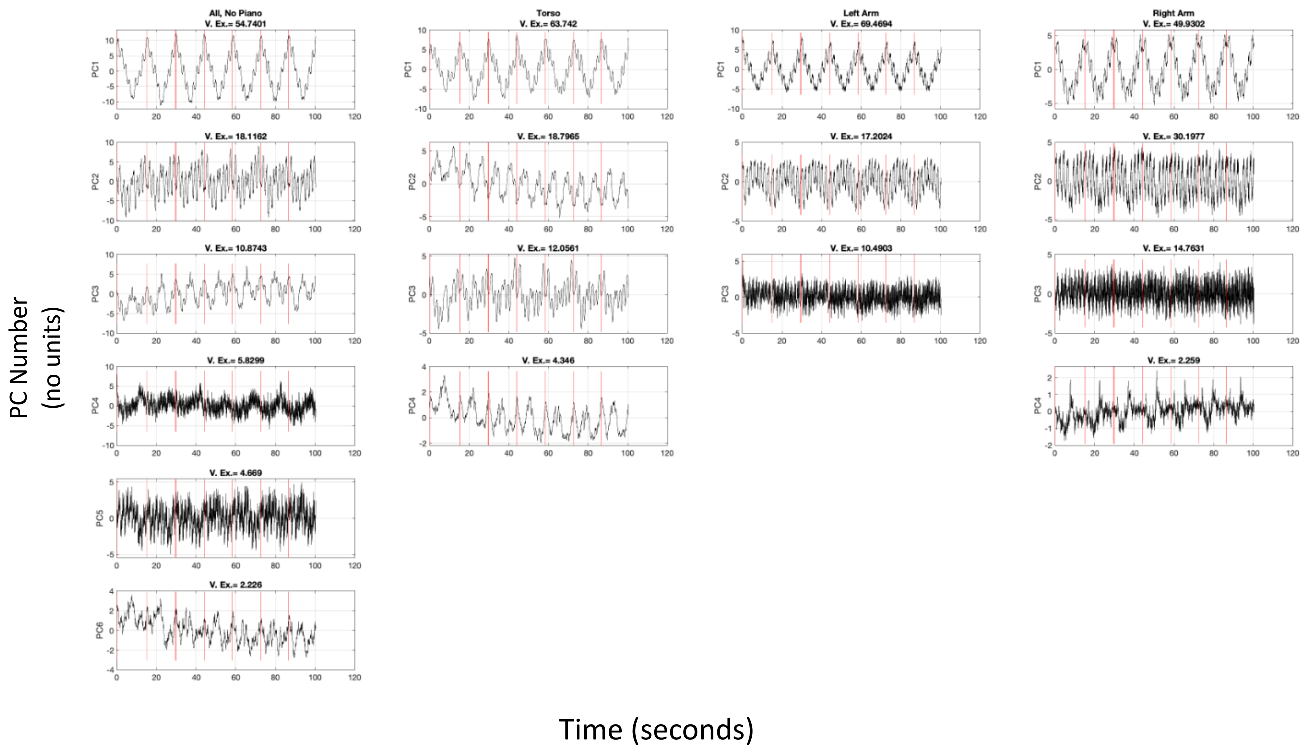
Motion Trajectory Plots for the Blocked Octaves Task, Participant 4, Trial 1 (mm.)



Note. Blue trajectories correspond to head markers. Black trajectories correspond to spine and pelvic markers. Green markers correspond to the right arm and shoulder markers. Red markers correspond to the left arm and shoulder markers.

Figure 6.23

PC Waveforms from Torso, Left Arm, Right Arm PCAs for the Octave Task, Participant 4, Trial 1



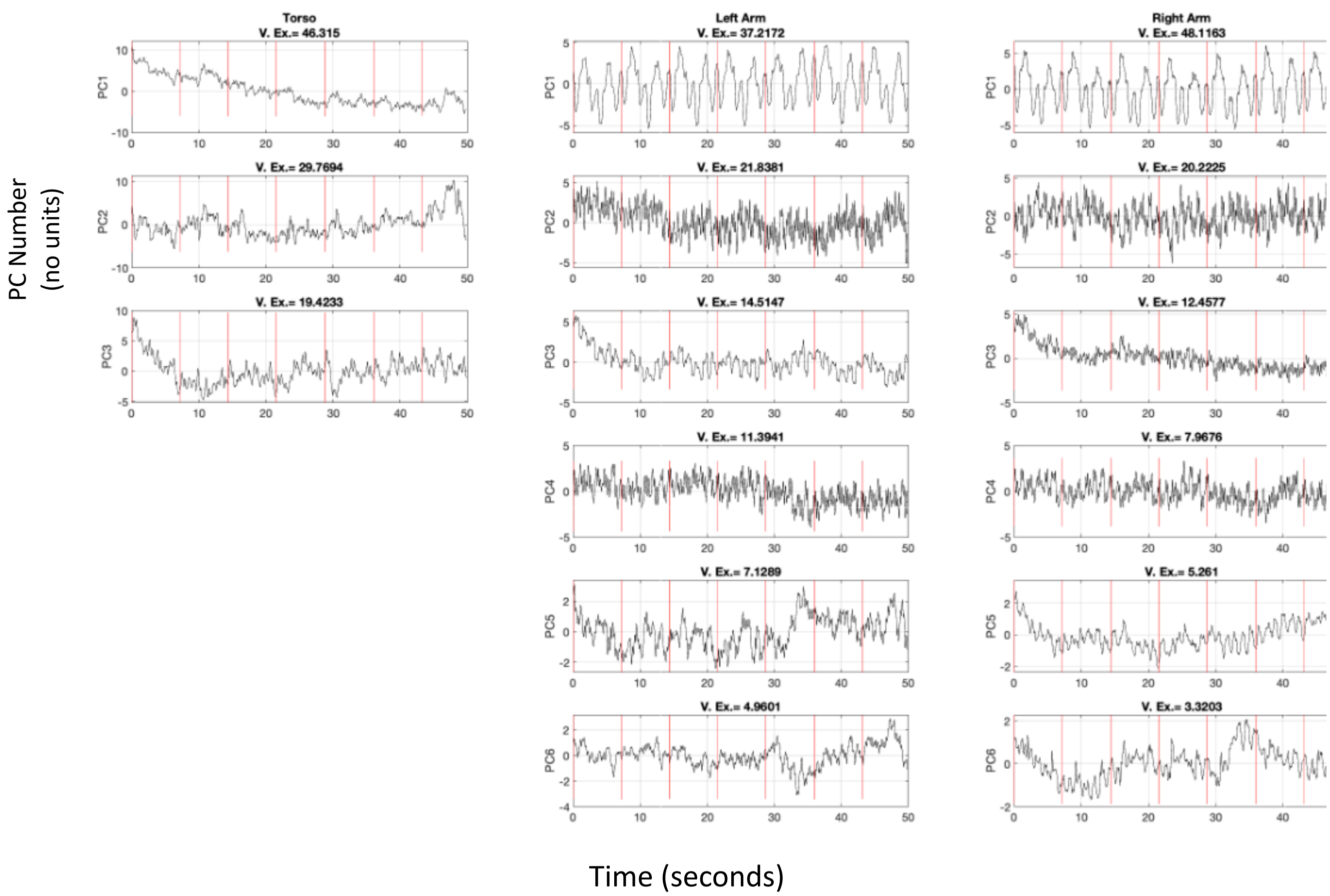
Note. The far-left column contains PC waveforms from the all-maker PCA. The middle-left column contains PC waveforms from the torso PCA. The middle-right column contains PC waveforms from the left arm PCA. The far-right column contains PC waveforms from the right arm PCA.

Interestingly, participant 4's unique cross-body coordination also persisted for the Symmetric 5ths exercise, which, like the octave task, requires the pianist to move their hands forward and backward on the keys to target groups of two white keys or two black keys. Whereas all other participants held the torso and head relatively stationary during for this task, letting the arms and shoulders extend forward to reach the black keys and retract backward towards the white keys, participant 4 rocked on the pelvis to move the whole torso forward and backward to help carry the arms forward and backward. As in the preceding octave examples, participant 4's PC waveforms for this task exhibited coordination at the level of the task repetition and keypresses for the arms, torso, and all PCAs. Contrastingly, the PC waveforms of the other pianists exhibited distinct variation patterns for the torso and the arms (figure 6.24). The waveforms of participant 3 serve as an example of the qualities exhibited by the waveforms of the pianists besides participant 4 for this task.

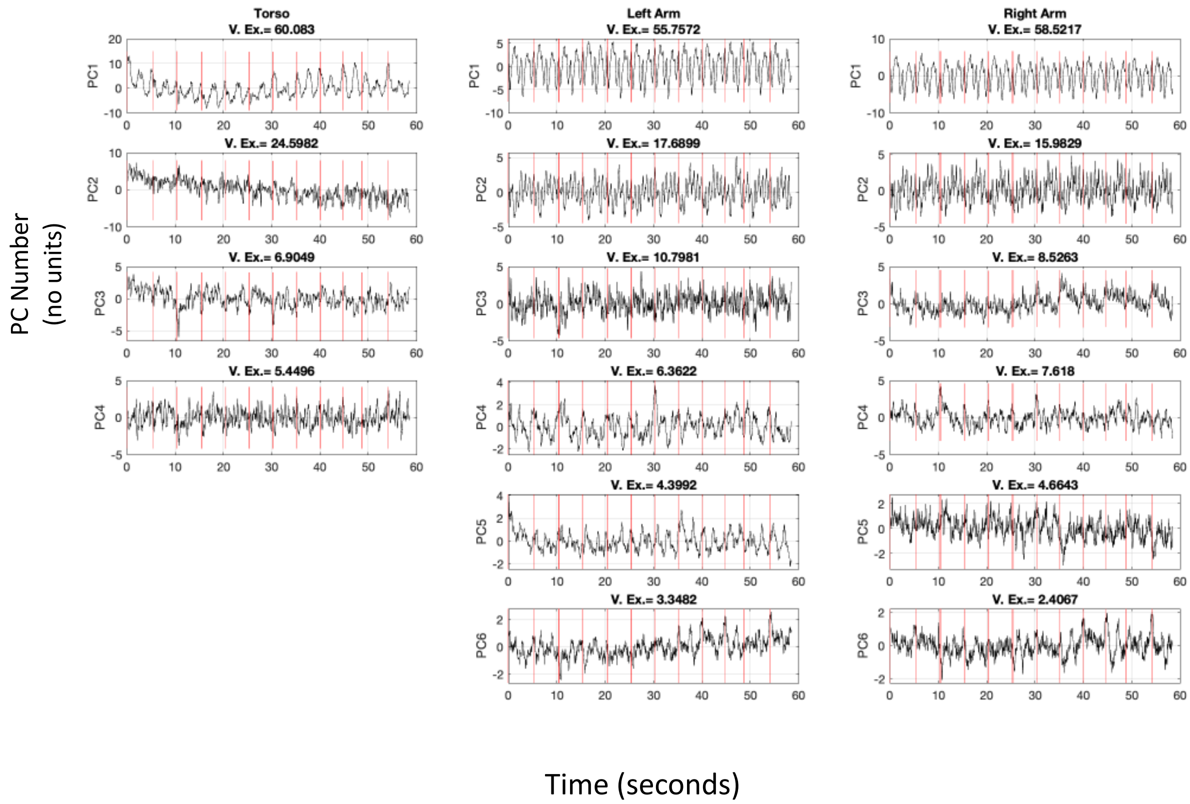
Figure 6.24

PC Waveforms from Torso, Left Arm, Right Arm PCAs for Symmetric 5ths Task from Participant3, Trial 1, and Participant 4, Trial 1

A) Participant 3 (Patterns are Similar for Participants 1, 2, 4, and 5)



B) Participant 4 (Patterns are Unique to this Participant)



6.5.3.1 Conclusions About the Impact of Biomechanical Functional Groupings. The examples presented in this section indicate that participant-specific coordination characteristics can be made clearer by examining the characteristics PC vectors conducted on independent functional groupings of markers created from subsets of the motion capture data. By dividing the motion capture data into subsets based on the possibility for some groups of markers to exhibit movement variation independent of the others, researchers can determine the degree to which the movements of various parts of the body represented by the subgroups are coordinated or move independently. We divided the motion capture data based into three functional groupings, representing markers on the torso, right arm and left arm independently.

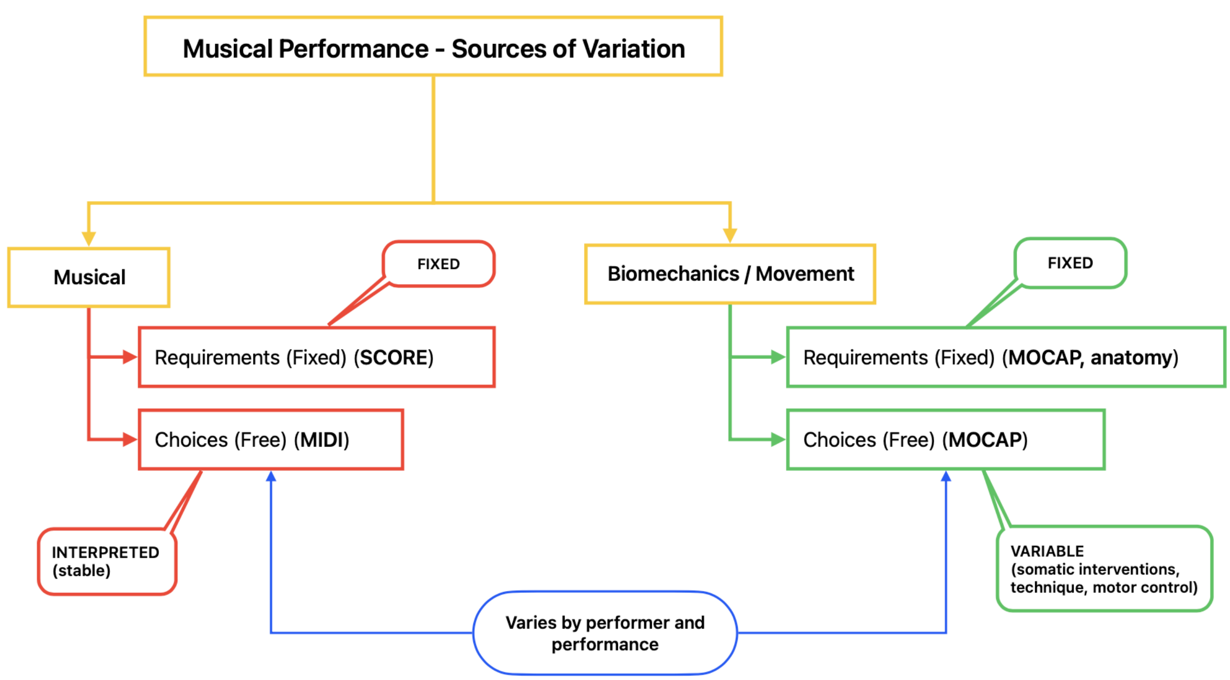
Future research could explore other possibilities for functional groupings depending on the biomechanical characteristics of the musical tasks or the overall research question.

6.6 Conclusion: Variability in Musical Performance- A Theoretical Framework

The analytical process of visual inspecting and comparing raw movement trajectories, MIDI plots, and PC waveforms of pianists' performances of different musical tasks help elucidate different sources of variation in the motion capture data. These include task-dependent variation related patterns encoded in the pitch and rhythmical parameters of the musical task, task-independent variation related to performer's idiosyncratic ways of organizing their movements, and variation related to independent movement of flexible but identifiable functional groupings of markers in different regions of the body. The analysis suggested that often the many layered sources of variation obscure researchers' ability to target variation related to pianists' unique coordination characteristics. The most dominant form of variation appears to be that related to musical task parameters, since in almost all cases the first PC strongly resembled the variation characteristics of the musical tasks themselves, and since frequency content at the frequency of task repetitions or keypresses are often visible throughout all PCs, whether they describe a large or small amount of the overall variance. Since PCA gives a mathematical accounting of all variation in a data set, regardless of the sources of variation, taking PCA further as a means of analysing subtle fluctuations in coordination characteristics of pianists requires that researchers take a detailed accounting of these different sources of variation contributing to a musical performance. Applying PCA in repeated measures studies examining coordination characteristics also requires consideration of which sources of variation are free to vary based on the choices of the performer, and which sources of variation are fixed requirements of the task that are invariant between performers and repeated performances from the same performer. To help organize the development of new quantitative procedures for applying PCA that targets intra- and inter-individual differences in coordination characteristics, we draw on the evidence from the observations of this study to propose the following 'theoretical framework of variation in musical performance' as a way of organizing and categorizing different sources of variation layered in music motion capture data (figure 6.25).

Figure 6.25

A Theoretical Framework of Variation in Music Performance



This framework organizes the primary sources of variation contributing to a musical performance into two categories: (1) musical sources and (2) biomechanical sources related to performers' movements. Musical sources of variation can be divided into two sub-categories: (1) musical task requirements, as dictated by the musical score or musical parameters imposed by the researcher, and (2) musical choices. Musical choices reflect the variation in tempo, timing, articulation, and loudness chosen consciously or unconsciously by the performer as they produce their interpretation of the musical requirements. In the context of performances reflecting musical scores or pre-defined musical tasks (*i.e*., not improvisations), variation related to musical requirements will be invariant across performers and performances of the same task, provided the performers remain faithful to task requirements. These requirements usually dictate the music's pitch and rhythm content, along with timing and dynamic changes specified by the composer. Therefore, variation generated by musical task requirements represents a type of variation that does not provide information about the changes in the coordination characteristics of pianists, yet would be present in all motion capture data submitted to PCA analysis of performers' movements, regardless of which pianist is playing or which experimental condition the performer is playing in. The variation introduced by musical choices is expected to vary between performers and performances, based intra-individual differences in expressive interpretations. Only a fraction of the fluctuations in dynamics, articulation, and timing that add dimension and shape to the music are notated in the score. Many changes to dynamics and expressive timing are generated by the pianist themselves using knowledge of the sense of style and musical structure to generate smoothly shaped phrasing and aesthetically pleasing changes in timing. This kind of musical variation is flexible and could be changed according to the choices of the performer. However, in practice, most pianists' musical interpretation will stabilize for a given musical task over many repetitions (Caramiaux et al., 2017) and pianists can adopt their own unique approaches to expressing the underlying musical structures (Repp, 1990). Variation introduced by task requirements related to the musical score are considered 'fixed' sources of variation, since they are expected to be present in the data of any pianist performing that task. This fixed variation can be defined prior to data collected and analysis by studying the variation characteristics of the pitch and rhythm data using MIDI. Variation related to aesthetic musical choices are considered a 'free' source of variation, because they cannot be controlled or defined prior to the spontaneous performance of the musician. Information on the musical choices made by the performer is also contained in the MIDI data, which encodes information about pitch loudness and timing.

Biomechanical/movement sources of variation in music performance can be divided into two categories: (1) required movement variation resulting from anatomical constraints, and, in the case of motion capture studies, the arrangement of anatomical markers positioned on the body to represent anatomical structure, and (2) variation resulting from the ways performers choose to move from among the many possibilities afforded by the degrees of freedom available in the musculoskeletal system and the adaptability of the psychomotor system. Movement variation resulting from anatomical features and the placement of anatomical markers on pianists' bodies will remain largely 'fixed' across pianists and between repeated performances. This is because the structure of human musculoskeletal system constrains the possibilities for the degrees of freedom available to each joint and locks some anatomical markers into invariant coordinated relationships. For example, markers placed on the distal processes of the ulna and radius on the wrist, the third metacarpophalangeal joint on the hand, and the lateral epicondyle of the humerus will share characteristics of movement variation because they are attached to the same limb. Whenever the hand translates in space, all markers on the hand, wrist, and arm will move together. Although it is possible for the wrist to bend, flex, and deviate independent of the forearm, and the wrist markers can rotate independently of humerus due to the proximal and distal radio-ulnar joints, some of the variation contained in movement will be common among all anatomical markers of the arm during the translation of the hand. Since the people included in the study have the same general arrangement of limbs and joint functionality, the variation related to anatomical constraints will remain consistent between pianists performing the same musical task, although the distance between markers will be scaled based on bone length/size of individuals. Variation relating to constraints imposed by the structure and function of the human body does not highlight intra- and inter-individual differences in coordination characteristics. This type of variation also cannot be influenced by movement retraining interventions; no matter how much movement training an individual does, the overall shape of the skeleton and attachments of muscles to the skeleton will remain unchanged. This type of variation is considered 'fixed' because it can be controlled for and defined prior to performance of the musical tasks.

6.7 Discussion: Extraneous Factors Influencing Variability in Piano Performance

Due to the numerous possibilities for coordinating the various degrees of freedom afforded by the human musculoskeletal and psychomotor systems it is possible for pianists' movements to vary widely in executing task requirements during a musical performance. Pianists' movement choices may be influenced by several factors, such as the pianists' previous training (Hadjakos & Mühlhäuser, 2010), the presence of pain or injury (Kaufman et al., 2018.), or physical fatigue (Goubault et al., 2021.). The pianists' degree of expertise will also influence movement variation; as pianists become more skilled, they tend to employ greater flexibility and diversity of movements (Furuya & Altenmüller, 2013; Goebl & Palmer, 2013). Less experienced pianists may freeze degrees of freedom to contend with task complexity, limiting movement variation. Similarly, pianists' movement strategies may evolve as they learn to execute a movement task that they find difficult at first. Through practice, they will be able to adjust their movement strategies to execute a performance task more successfully, gradually stabilizing coordination patterns so they become more organized and variation becomes more task-relevant (Wu et al., 2014.). Pianists' movement choices may also be influenced by changing performance conditions, such as performing on an unfamiliar instrument, or performing in stressful situations, such as exams or competitions (Bragge et al., 2006). It is this type of variation (variation related to choices in movement strategy) that is most flexible and susceptible to influence by movement retraining interventions, and therefore of most interest to researchers studying how such interventions may lead to changes in coordination characteristics of pianists. Furthermore, changes to musical interpretation can be linked to changes in movement strategies since the musical sounds are generated by a transfer of energy from the movements generated by the performer's muscles to the lever system of the piano key. This relationship means that small adjustments to movement strategies can lead to audible changes in musical variation. It is theorized that audible improvements to musical performances following movement retraining interventions may arise from pianists' ability to adjust their choice of movement strategies to greater control and variety of musical sounds. This relationship is reflected by the blue arrow in figure 6.25.

Organizing sources of musical variation using our framework provides a theoretical basis for considering the different sources of variation that contribute to a musical performance and helps identify the specific sources of variation that are sensitive to manipulated variables in experiments. Discovering how pianists' coordination characteristics evolve in response to movement retraining requires researchers to focus on analytical techniques for tracking and measuring changes to variation related to biomechanical/movement choices, and any related variation in musical choices. This framework also clarifies why using PCA to study subtle differences in pianists' coordination characteristics poses analytical issues that need to be addressed: when collecting motion capture data on pianists, variation will be present from all sources and PCA will generate PCs reflect variation from all sources simultaneously. Since each component contains variation from all variables, is not feasible to separate the sources of variation from individual principal components after a standard PCA has been conducted. Therefore, it may be difficult to distinguish the degree to which changes in movement choices are reflected in the PCA results comparing musical performances without finding a means of controlling the presence of other source of variation in the data set prior to conducting PCA. Reflecting on whether the different sources of variation represented in the framework are fixed or free to vary for a particular performing context will guide researchers developing mathematical strategies that could help PCA target variation related to either biomechanical and/or musical choices. The following section proposes possible solutions for managing the competing sources of variability in the data set to be investigated in future studies.

6.7.1 Future Strategies for Managing Variation Sources in Music Performance to Study Coordination Characteristics of Pianists Using PCA

If PCA is to prove useful in tracking and measuring subtle changes in coordination characteristics of pianists in response to movement retraining interventions, future research must develop strategies for targeting free variation related to performers' musical and biomechanical choices. To address this problem, we are developing mathematical solutions for removing task-determined variation from the dataset prior to conducting PCA. Such solutions will permit researchers to highlight the more subtle variation patterns related inter- and intra-individual differences, or changes in experimental conditions. We propose that a mathematical solution to this problem can be devised by creating a task-model to represent fixed variation patterns using the MIDI data. MIDI data related to pitch and note timing is directly linked to musical task constraints and could be used to create a dataset containing the variability characteristics modeling task requirements. A solution will be devised using linear algebra to project the motion capture data of a trial onto a subspace represented by a task model constructed from MIDI data. This process would produce a transformed original data set that contains only variation perpendicular to the subspace represented by the MIDI data. The transformed dataset would represent variability in the motion capture data that is independent of the variation represented by the MIDI data, allowing researchers to examine the variation in the dataset related to factors outside of musical task constraints. This process will be further developed in our subsequent research.

Our future research will also seek solutions to address fixed sources of variation related to biomechanical constraints by expanding on the practice of conducting multiple independent PCA on subsets of markers introduced in this paper. Our visual observations of the data presented in this study suggest that it may be possible to identify invariant PCs present in multiple subsets of the data representing different regions of the body separately, such as the right and left arm, the pelvis, the torso, and the head. Although a comprehensive visual assessment of the data was integral to helping form the theoretical concepts outlined in the

Theoretical Framework of Variability in Music, visual observations cannot quantitatively define the degree of similarity between PCs from different data sets. Future work presented in article five of this thesis presents a mathematical approach that can quantitatively verify the similarity of PCs suspected as being similar using visualization. Objectively demonstrating the existence of these invariant PCs across independent PCAs on subsets of motion capture data would essentially identify linear subspaces that represent variation independent of other variation contained in the data. Identifying these subspaces will provide an approach to linking specific variation patterns to specific groups of markers, enhancing the biomechanical interpretability of the PCs. It may also be possible to examine characteristics of the weighting matrices of invariant PCs to draw more precise links between certain motion trajectories and the PC waveforms.

Another possible way of managing the impact of variation related to fixed biomechanical sources is to reduce biomechanical redundancy in the variation of the data by focusing on a subset of the x, y, z trajectories that have high correlation coefficients. In this case, replacing the data matrix columns with a group of linearly combined variables exhibiting similar movement patterns in certain planes would result in a data set with fewer dimensions and less biomechanical redundancy. Running a PCA on a dataset with fewer biomechanical redundancies may influence the results of the PCA, potentially impacting the characteristics of the PCs and their ranking in terms of the amount of variation they explain. It may also help clarify whether any components relate to clearly identifiable biomechanical features in the movement.

6.8 Concluding Summary

The dominance of fixed biomechanical and musical patterns in the movement data and subtlety of variation related to performers' freely varying movement choices distributed throughout the body result in a complex dataset in which the underlying sources of variation cannot easily be disentangled for study. Our future research will explore novel PCA protocols that more rigorously consider the competing sources of variability in the motion capture data of pianists to enhance its ability to detect evidence of change to pianists' coordination characteristics related to movement retraining. The newly proposed theoretical framework of variation in musical performance can help to guide future researchers in the development of new PCA methodologies that contend with the layered sources of fixed and free variation in data from musical performance. Continuation of this research will contribute new approaches to PCA which may be better suited for detecting evidence of subtle changes to pianists' coordination patterns that could be applied in future studies on movement re-training programs seeking to help pianists learn to move more comfortably.

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Appendix A

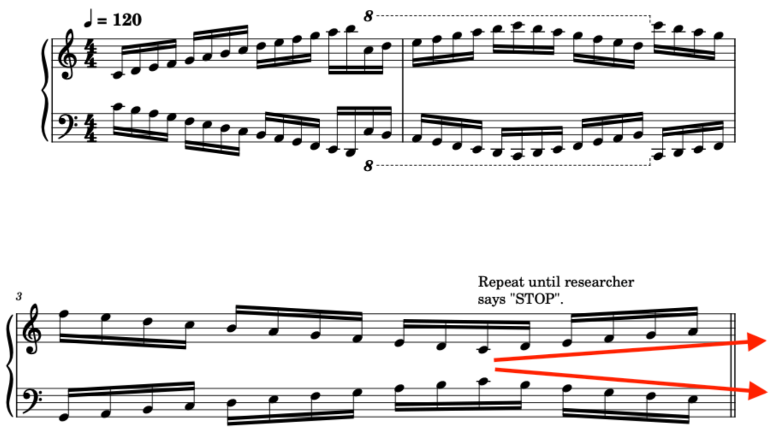
Full List of Musical Tasks

1) Contrary Motion C Major Scales, Three Octaves.
2) Parallel Motion C Major Scales, Three Octaves
3) 5-Finger Passage, Six Octaves
4) Two Note Slurs, Contrary Motion.
5) Whole Tone Scale in Blocked Octaves, hands together, full length of keyboard, ascending and descending.
6) Alberti Bass Passage with Alternating Right Hand and Left Hand Eighth Notes
7) Chromatic 5-Finger Passage for Right Hand. Exercise 12a) from Béla Bartók's *Mikrokosmos, Volume II* (p.42)
8) Chromatic 5-Finger Passage for Left Hand. Exercise 12b) from Béla Bartók's *Mikrokosmos, Volume II* (p.42)
9) Parallel Fifths Exercise 17a) from Béla Bartók's *Mikrokosmos, Volume II* (p.43)
10) Symmetric Fifths Exercise 17b) from Béla Bartók's *Mikrokosmos, Volume II* (p.43)
11) *Valse Mignonne,* in *Album pour la jeunesse, Op. 23* (1906) by Henryk Pachulski

Musical Tasks Highlighted in This Study

1) **Contrary Motion C Major Scales**

Performance instructions: Play repeatedly at a tempo of your choosing until the researchers says “stop”. Play without the musical score.



2) **Parallel Motion C Major Scales**

Performance instructions: Play repeatedly at a tempo of your choosing until the researchers says “stop”. Play without the musical score.

3) Whole Tone Scale in Blocked Octaves

Performance instructions: Play repeatedly at a tempo of your choosing until the researchers says "stop". Play without the musical score. Use fingers 1 and 5 for all octaves.

4) **Symmetric Fifths Exercise 17b) from Béla Bartók's *Mikrokosmos, Volume II* (p.43)**

Performance instructions: Play repeatedly at a tempo of your choosing until the researchers says "stop". Play while reading the musical score. Play all fifths with fingers 1 and 5.

CHAPTER 7: ARTICLE 5

Functional Subspace Identification: A Technique for Assessing Coordination Characteristics in Complex Tasks by Locating Invariant Principal Components in Subsets of Movement Data

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Abstract

PCA (principal component analysis) has shown promise as a tool for dimensional reduction in motion capture data sets to better understand underlying patterns of variation related to coordination characteristics in human movement. However, the presence of multiple overlapping sources of variability in the data set makes it difficult to interpret the biomechanical relevance of variation characteristics described by individual PCs (principal components). Complex data which contains a high number of complex sources of variation exacerbates this problem. A high level of complexity is unavoidable when studying pianists' coordination characteristics in the context of authentic, bimanual musical performance due to the presence of multiple fixed sources of variation related to the defined musical and biomechanical task parameters, and flexible sources of variation related to the performers' musical and biomechanical choices (Beacon, Russell & Comeau, 2023a; Beacon, Russell & Comeau, 2023b). This paper proposes a novel solution to this problem based on the identification of invariant one-dimensional PC subspaces common to independent PCAs conducted on different subsets of motion capture data organized according to functional groups. Using the process of functional subspace identification, our research has identified examples of these subspaces relating to both task-dependent and participant-determined variation in piano performance data. The significance of these subspaces is discussed in terms of their ability to identify participant-specific coordination characteristics hidden in the overall movement variability that can be monitored over time. The number and characteristics of these subspaces could provide a means of tracking changes to pianists' coordination characteristics in response to movement retraining interventions such as the Feldenkrais Method® that seek to subtly reorganize movement coordination across the body. We present examples of task-dependent and participant-specific PC subspaces and discuss solutions for removing pre-existing musical patterns as our next research step.

Keywords: principal component analysis, PCA, complex movement analysis, functional subspace identification*,* coordination characteristics, motion capture, piano performance

Functional Subspace Identification: A Technique for Assessing Coordination Characteristics in Complex Tasks by Locating Invariant Principal Components in Subsets of Movement Data

Jillian Beacon, Donald Russell, Gilles Comeau

7.1 Introduction

PCA (Principal Component Analysis) is a mathematical method of representing data sets based on their variance that has been previously applied in human movement research as a means of reducing data dimensionality to identify fundamental variation characteristics and to distinguish them from residual variation (Daffertshofer et al., 2004). Current approaches for conducting PCA on human movement data are well documented in existing tutorials (Daffertshofer et al., 2004; Federolf et al., 2014; Federolf, 2016; Forner-Cordero et al., 2005; Shlens, 2014). PCA has been successfully applied to gain insight into fundamental variation characteristics of repetitive movements such as gait (Chester & Wrigley, 2008; Reid et al., 2010), cycling (Skaro et al., 2021), and swimming (Andrade et al., 2018). PCA has also been used to compare movement characteristics between experimental groups where a large difference in movement quality is expected, such as between novice and elite athletes (Ross et al., 2008), fatigued and unfatigued jump ropers (Bruce et al., 2017), or people with and without motor control disorders such as Parkinson's Disease (Dillmann et al., 2014).

Considering these previous applications, we propose that PCA will be useful for gaining insight into how complex movements, such as piano playing, vary over time, and how pianists respond to pedagogical and therapeutic training interventions. Some researchers have already used PCA to examine characteristics of pianists' movement. For example, Buck et al., (2013) and

MacRitchie et al., (2013) used PCA to examine unique coordination profiles related to expressive timing in pianists performing two Chopin Preludes. Tits and colleagues also used PCA to compare the number and characteristics of PCs (eigenmovements) in the hand movements of pianists of varying levels of expertise (Tits et al., 2015). More recently, Walton (2016) used PCA to determine performance conditions that promote synergistic movement patterns in two improvising pianists. Although these studies successfully applied PCA as means of understanding high-level features of movement variation related to piano-playing characteristics, they did not consider how PCA on its own cannot distinguish between various underlying sources of variation in the data that might influence the results. For instance, in the case of musical performance, the musical task parameters contribute defined variation patterns based on the established musical characteristics of the task. Variation from task-determined characteristics is layered with variation related to individuals' musical and biomechanical choices. Existing studies using PCA with pianists have not controlled for the various sources of variation in a way that would permit targeted identification of variability related to specific coordination characteristics, making it difficult to use PCA as a means of tracking changes to coordination characteristics over repeated trials.

Before PCA can be applied as an analytical tool for tracking and measuring changes to pianists' movement characteristics over time, researchers must arrive at a better understanding of how the many different types of variation present in motion capture data from musicians influence PCA results and propose new PCA procedures that can help target variation related to participant-specific musical and biomechanical choices (Beacon, Russell & Comeau, 2023b). This present paper proposes a novel solution to this problem based on the identification of invariant one-dimensional PC subspaces common to independent PCAs conducted on different subsets of the motion capture data organized into functional groupings. Our proposed functional subspace identification approach involves dividing a complex data set of motion trajectories into functional subsets of variables that may form independent moving subsystems within the larger group based on biomechanical features of the human body. Conducting independent PCAs on functional subgroups permits comparison of the shape of PC vector waveforms from different PCAs to search for invariant patterns unique to individual participants or tasks. This study identifies examples of these subspaces in piano performance data from different performers and different musical tasks and discusses how future research could expand this strategy as a means for tracking participant-specific coordination characteristics in future intervention studies with pianists.

Finding strategies for identifying coordination characteristics in complex motion capture data sets including many variables distributed throughout the body is a central challenge facing human kinetics researchers. Functional subspace identification could provide a solution to this problem that may also benefit researchers studying movements outside of the context of music performance. The examples presented in this paper demonstrate the potential for functional subspace identification to help PCA become a more targeted tool capable of identifying specific coordination features of individuals that can be tracked over time, rather than a tool for making general observations about the movement features related to broad experimental groups.

7.1.1 Review of Literature

Our previous work suggests that standard PCA provides a high-level summary of movement variation characteristics related to the general act of piano playing, but it does not offer a means of distinguishing between task-determined and participant-determined variation in complex data sets (Beacon, Russell & Comeau, 2023a). We also found that motion capture data of pianists contains many layered sources of variation that are difficult to separate using standard PCA procedures typically applied in human kinetics research (Beacon, Russell & Comeau, 2023b). Some aspects of the variation are fixed by task requirements while others are free to vary flexibly in response to performers' choices. Therefore, standard PCA is not an adequate means of studying variation related to participant-specific coordination characteristics in complex movements, such as piano playing. Previous researchers using PCA to study human movement have contended with the impenetrability of variation in complex data sets by either limiting the number of variation sources introduced to the PC by simplifying task requirements and reducing analysis to a simpler subset of kinematic variables (Furuya & Soechting, 2012; Gonzalez-Sanchez et al., 2019; Verrel et al., 2013) or by conducting PCA on a complex data set consisting of whole-body kinematic variables during authentic performances of complex movements and using statistics to find trends in the PCA data (Buck et al., 2013; MacRitchie et al., 2013; Tits et al., 2015; Walton, 2016).

Many of the studies using PCA to study whole-body or multi-joint systems have employed stacked PCA techniques (Troje, 2002) in which an initial PCA is conducted on motion capture data from individual participants, then followed by a second global PCA in which PCA-derived variables from all participants (such as PC component vectors or weighting vectors) are included. This approach has succeeded in finding patterns between PCA-derived variables and the degree of performance expertise in various complex movements. For example, Zago and colleagues (2017a) conducted PCA on full-body motion tracking data (14 body landmarks) of ten professional and amateur karateka performing a sequence of *kata* (traditional karate movements) and found that the principal movements derived from PCA varied among the participants as a function of their number of years of experience (Zago et al., 2017a). They were able to deduce a relationship between principal movement characteristics and expertise by applying a linear regression to variables derived from a second PCA conducted on a data matrix comprised of each karateka's eigenvectors (PCs), weighting curves, centre of mass kinematics, and 3D body coordinates. A related study by Zago and colleagues (2017b) compared the movements of six expert and six intermediate jugglers by conducting PCA on full-body motion capture data comprising 23 anatomical markers, followed by a global PC on all posture vectors (PCs) (Zago et al., 2017b). They found that the relative variance contributed by individual principal components changed as the juggling tasks became more complex. When the juggling task was simpler, involving only three balls, expert and intermediate jugglers had similar relative variance between components. As the task became more complex by adding additional balls up to five, intermediate jugglers were found to have a greater contribution of higher-order components (PCs of higher number) to the overall variance compared to experts. In other words, dimensionality of the data increased as the task complexity increased, but it increased more for intermediate jugglers compared to experts. It was also found that higher order components became less rhythmic (the PC patterns deviated from a regular timing cycle) as task complexity increased. Young and Reinkensmeyer (2014) used PCA to devise a method for predicting judges scores of divers competing in the 2009 World Diving Team Selection Camp. They performed PCA on two-dimensional video-based motion tracking data derived from a selection of eight anatomical markers. They then conducted a secondary PCA on a global matrix including the variables of all divers. The global matrix included PCA variables, such as the eigenposture vectors and eigenposture weighting curves, as well as variables related to visual indicators important to dive judges, such as body center coordinate vector, splash area vector, and board tip coordinate vector. Using regression methods, they were able to generate dive scores comparable to human judges. Interestingly, they found that the accuracy of the score prediction decreased the most when removing variables related to splash area and board tip movement, suggesting judges rely more on these environmental visual indicators to score diving than on divers' body postures. In fact, removing the eigenpostures from the algorithm slightly improved the agreement of the PCA-based scores with the judges' scores. The stacked PCA approaches described in these three studies are useful to distinguish movement characteristics between groups that are expected to differ significantly in performance ability, such as comparing experts and novices, or to identify common movement characteristics in a homogeneous group of performers. Conducting a second global PCA on a data matrix concatenating PCA variables from all participants provides a means of comparing movement characteristics across participants, but not a means of identifying subtle and unique coordination characteristics in individual participants or of measuring how coordination characteristics evolve over time in response to movement retraining interventions.

Complex signal processing of motion capture data is a burgeoning field in current human kinetics research, and many researchers are proposing different solutions for using PCA to study complex motion data in specific movement scenarios. For example, Forner-Cordero and colleagues (2005) have investigated the possibility of using PCA to study inter-joint phase relationships between more than two joints. This approach is most useful for studying repetitive movements in which specific inter-joint phase relationships are constant and can be predicted, such as swimming strokes (Seifert et al., 2014). It is less useful for studying movement characteristics across the whole body since there would be too many joint relationships to compare and since those joint relationships may not have predictable phase relationships. Another new area of research is functional data analysis, of which functional fPCA (functional PCA) is a promising technique for enhancing the interpretability of PCA in the study of multi-joint systems. This approach involves representing the data as a series of functions, then conducting the PCA on the set of functions instead of on the raw data (Warmenhoven et al., 2019a; Warmenhoven et al., 2021). This approach has shown promise in the study of inter-joint coordination in repetitive and cyclical movements, such as rowing (Warmenhoven et al, 2019b). As an analytical tool, fPCA is best suited to repetitive movements with structures that can be broken down into individual frequencies or functions that are superimposed. Unfortunately, many forms of complex movement researchers would like to study are not well-suited to functional analysis. This could be because they are made up of a series of discrete movements with different coordination characteristics, as in the execution of karate forms (Zago et al., 2017a). It could also result when movements are coordinated to an externally imposed pattern which may or may not contain repetitive structures over multiple timescales, such as dancing to music (Hollands et al., 2003) or performing with musical patterns (Walton, 2016).

Studying coordination characteristics during the performance of musical tasks requires novel solutions to penetrate the unique complexity introduced by the imposition of musical patterns encoded in pitch and rhythm. When it comes to studying pianistic movement, researchers must be able to examine how the movement of the head, torso, and arms relate, acknowledging that the right and left arms may each have unique movement characteristics or may be performing distinct patterns. Furthermore, the artistic nature of musical performance requires a flexible definition of a “successful performance” within an aesthetic range and may differ between performers or between successive performances by the same musicians. In many other highly skilled physical pursuits, the performer or athlete has the goal of replicating ideal movement characteristics that will lead to a consistent and predictable outcome. For instance, a rower may focus on executing specific postures, timings, and muscle recruitment strategies for maximizing the power of their stroke in each cycle (Warmenhoven et al., 2019b). A karateka may focus on executing each kata posture with proper alignment, speed, timing, and muscle recruitment for ultimate power and precision (Zago et al., 2017a). A high diver may plan the precise number of footsteps required to get to the end of the diving board, perfecting specific timing of body postures that will allow them to execute the dive parameters in time to enter the water seamlessly (Young & Reinkensmeyer, 2014). In these examples, the precise execution of movements themselves is the outcome desired by the athlete. The success of the outcome can often be measured by measuring the movement itself. In contrast, pianists are generally focused more on the musical outcome resulting from their movements and they may or may not consciously plan specific movement strategies for executing a musical task. Pianists generally judge their success by the quality of the musical outcome, and not necessarily the quality of the movement used to create the sound. In this sense, using PCA to study musicians' movement (in this case, pianists) has much in common with studying dance movements, in which variation in movement can arise from stylistic interpretation and artistic experimentation (Vincs & Barbour, 2014).

7.1.2 Purpose

The present paper proposes a novel solution for using PCA as a means of identifying both task-dependent and participant-determined coordination characteristics in pianists' movement during the performance of various musical tasks. The proposed approach, referred to as *functional subspace identification*, capitalizes on the fact that even though PCA algorithms assume independence of all variables included in the data matrix (Daffertshofer et al., 2004), in practice, the movement variation of individual anatomical markers fixed to the body can be related by several physiological and psychomotor factors. One of these factors is the functional independence of different rigid bodies afforded by various joints. For instance, when a person translates their entire arm in space by moving the humerus in relation to the scapula, the movement variation of all anatomical markers attached to the arm will be related. The physical structure of the human body and the flexibility of the sensorimotor system that controls its movement allows for parts of the body to move independently. For instance, the physical structure of joints permits that the right arm can move independently of the left arm, the arms can move independently of the torso, and the head can move independently of the spine and arms. The psychomotor system can flexibly coordinate available degrees of freedom, allowing various subsystems of anatomical markers to move independently or together, depending on the task. The way in which various parts of the body are coordinated to move independently or together can be influenced by training, experience, task constraints, environmental factors, age, or the presence of motor control disorders.

Independent control of the torso and each arm is essential to piano playing since each hand must be capable executing distinct musical patterns simultaneously. Pianists adapt coordination characteristics moment to moment to execute the artistic and technical aspects of musical tasks. Since independent coordinative relationships could exist within the larger system of all anatomical markers, it is possible that PCA could be used to identify variation patterns related to specific functional subgroups of markers. In our previous work, visual inspection revealed common PC waveforms arising from separate PCAs on subsets of markers selected based on coordinated functional groupings, including: (1) PCA^{torso}, including only the torso markers (pelvis, spine, head); (2) PCA^{left}, including only the left arm markers (acromion, elbow, distal ulna, distal radius, and the third metacarpophalangeal joint); and PCA^{right}, including only the right arm markers (same landmarks as for the left arm) (Beacon, Russell & Comeau, 2023b). This suggests the larger data set contains groupings of variables with sub-coordinative structures that display properties of independence that remain consistent, even when other markers are removed from the PCA. Exploring the visual landscape of the PC waveforms suggested that the shape of the waveform can be used as a way of identifying persistent PCs. Based on these observations, we hypothesized that comparing PC waveforms resulting from all the motion capture trajectories to waveforms from subgroupings based on functional groupings of anatomical markers would reveal patterns which persist in the data as a whole and in specified functional groupings.

To that end, we hypothesized that conducting independent PCAs on functional subgroups and comparing the resulting PC vectors in pairs by calculating the angle between them would reveal invariant PCs existing in two or more independent groups of markers. PC pairs separated by very low angles would represent similar “directions”, or subspaces, in the dimensional space of the matrix from which they were derived. PCs common to two datasets represent invariant one-dimensional PC subspaces describing independent variation common to each dataset. The mathematical process of computing the angles between PCs has been previously described (Golub & Van Loan, 2013). Previous researchers have used angle comparisons of PCs to locate PC subspaces in motion-capture data of right arm joint movements concatenated from multiple participants to determine three-dimensional joint-synergies in catching movements (Bockemühl, Troje, & Dürr, 2010; Dubois et al., 2023). In this case, computing the angles between PCs helped to determine sets of PCs that better summarize the task-related features of simple throwing movements. This approach has not yet been used to compare PCs between subgroups of motion-capture data from more complex movements to identify coordination characteristics unique to individuals. The existence of one-dimensional PC subspaces between independent functional groups of motion capture data would suggest that a coordinative relationship exists between the functional subgroups even though they do not share common data. Alternatively, the absence of invariant PCs between functional subgroups could indicate that the groups move independently of one other, and do not share variation characteristics. The PCs from a PCA conducted on an independent functional subgroup ($PCA^{subgroup}$) can also be compared to the PCs of a global PCA including motion capture data from the entire body (PCA^{all}). Identification of an invariant PC common to both PCA^{all} and a

$PCA^{subgroup}$ would point to the existence of a one-dimensional PC subspace within the larger data set arising from independent movement variation related to the markers included in the functional subgroup. Since these subspaces would be linked to a subset of marker trajectories within the greater data set, their meaning could be interpreted with a greater degree of biomechanical precision than PCs derived from the entire data set alone.

The purpose of this paper is to present evidence that these previously unidentified one-dimensional PC subspaces exist among PCA^{all} and $PCA^{subgroups}$ (PCA^{torso}, PCA^{left}, and PCA^{right}) conducted on the motion capture data of six skilled pianist performing various technical musical tasks. We present (a) evidence of invariant PC subspaces between PCA^{all} and $PCA^{subgroups}$ that point to the existence of independent coordinative subgroups within the full data set; and (b) evidence of invariant PC subspaces between independent functional subgroups that point to coordinative relationships between different subsets of anatomical markers. We discuss how these subspaces can be linked to coordination characteristics related to either musical task parameters or to participant-specific coordination characteristics. We present a method of objectively identifying PC subspaces by computing the inter-PC angle between pairs of PC vectors relating to subsets of motion capture data. We hypothesized that many of the identifiable subspaces occurring among PCA^{all} and $PCA^{subgroups}$ may occur as a result task-dependent PCs accounting for greater percentages of the overall variance in their respective data sets. These task-dependent PCs would likely be similar across all participants. Unique participant-specific PC subspaces may be found between higher-numbered PCs among PCA^{all} and $PCA^{subgroups}$, since higher numbered PCs are more likely to relate to participant-specific variation characteristics in the data, even though they account for a lower percentage of the total variance.

PC subspaces could be used as indicators of underlying coordination characteristics in motion capture data of pianists, which may be hidden in the layers of variation present in the data from multiple sources. In future research, the characteristics of these subspaces could be tracked over repeated trials to establish their consistency over time, and to determine whether they change in response to movement retraining interventions as pianists learn new ways to organize their movement. The functional subspace identification approach described in this paper is novel and has not appeared in previous literature. Further development of functional subspace identification techniques could provide a robust method for using PCA to study coordination characteristics in complex movement of musicians or non-musicians that provides information that can be physically interpreted based on coordinative relationships between functional anatomical groupings chosen by the researcher. This would help address one of the primary limitations of PCA, which is that it is often difficult to arrive at physical interpretations of the variation described by the PCs due to overlapping sources of variation.

7.2 Methodology

7.2.1 Participants

Six skilled pianists (four males, two females, ages 24-58, mean age: 35 years) participated in three motion capture sessions over three weeks, spaced one week apart. Although each pianist had extensive musical training, they had very different training histories. Participant 1 (age 32) began studying piano at the age of six and completed a Bachelor of Music in Piano Performance. They had completed piano pedagogy training at the master's level and worked as a piano teacher for fifteen years. Participant 1 had a history of playing-related pain in the left shoulder and in the C7-T1 nerve roots. They had sought many treatments over the years and managed symptoms using the Feldenkrais Method®. Participant 2 (age 29) began studying piano at the age of five and completed a Bachelor of Music in Music Composition and Theory. In addition to practicing and teaching the piano, they were also trained to play harpsichord and other baroque keyboard instruments. They had a history of tendinopathy in both arms that prevented them from playing for a period. They went on to manage symptoms using techniques of *The Taubman Method.* At the time of the study, the pain had resolved. Participant 3 (age 58) began studying piano at the age of eight and completed grade 10 Royal Conservatory exams in vocal and piano performance. They continued practicing piano but went on to specialize in organ performance, becoming an Associate of the Royal College of Organists. They reported no history of playing related pain. Participant 4 (age 43) began studying piano at the age of four achieved Licentiate Diploma in Piano Performance from the Royal Conservatory of Music. At the time of the study, participant 4 practiced and performed regularly with their piano trio and taught some piano students. They did not report a history of playing-related pain. Participant 5 (age 24) began studying piano at the age of 13 and was completing the final year of a Bachelor of Music in Piano Performance at the time of the study. They had developed playing related pain in both wrists during university and managed symptoms with practice strategies, rest, and somatic training from the Feldenkrais Method®. Participant 6 (age 26) began studying piano at the age of eleven and was beginning the first year of a master's degree in piano performance at the time of the study. They reported no history of playing-related pain at the time of the study but developed occasional soreness in the neck and left scapula during long practice sessions.

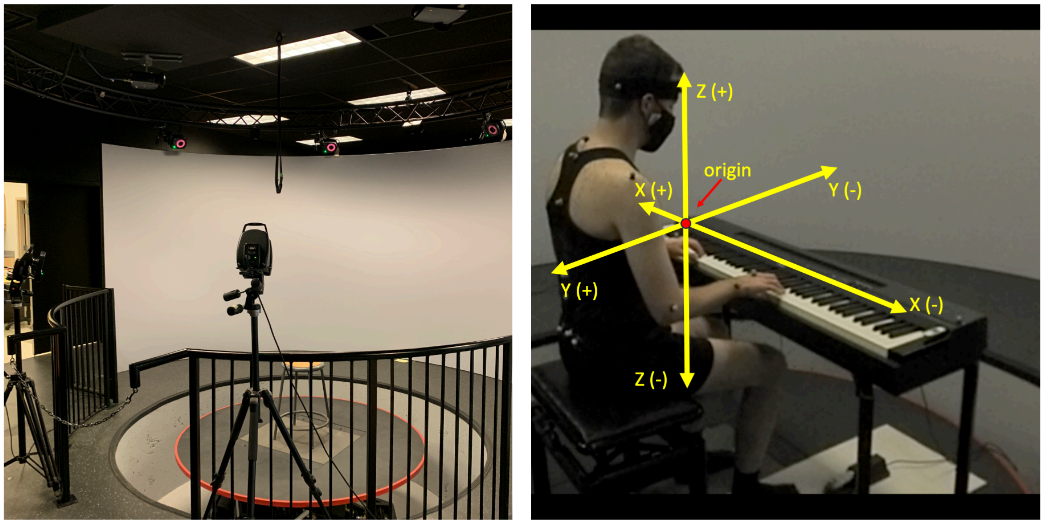
The lack of homogeneity in the musical training backgrounds of the participants was considered an asset to this study, since we were seeking to develop techniques for identifying unique coordination characteristics of pianists.

7.2.2 Apparatus

Pianists performed the musical tasks on a Yamaha P-255 digital piano, which collected MIDI (musical instrument digital interface) data of all the performances. 3D motion capture data was captured using a nine-camera Vicon system at a frequency of 100 Hz. The piano sat on a platform surrounded by a ring of seven ceiling mounted Vicon cameras. Two Vicon cameras were placed behind the performer to ensure accuracy of tracking of the spine markers (figure 7.1, left). The x, y, and z axes were defined using the piano marker placed at the front left-hand corner of the instrument as the origin (figure 7.1, right). Motion capture data was collected at a frequency of 100 Hz. Additional details concerning apparatus used in data collection have been previously described (Beacon, Russell & Comeau, 2023b).

Figure 7.1

Motion Tracking Platform, Orientation of Vicon Cameras and Definition of X, Y, Z Axes



7.2.3 Participant Preparation

The process for collecting the motion capture data for this study has been previously described (Beacon, Russell & Comeau, 2023a; Beacon, Russell & Comeau, 2023b). Each participant participated in three motion capture sessions over three weeks, spaced one week apart. Participants were given the musical tasks a week ahead of time to become familiar with and practice. During data collection participants wore black shorts and a tight-fitting black athletic top. Twenty-two reflective markers were positioned on anatomical landmarks on the head, shoulders, spines, hands, arms, sacrum, and pelvis of each participant (figure 7.2). The markers on the hands, arms, shoulders, and C7 were fastened directly to the skin with adhesive tape. The four head markers were fixed to a headband participants wore around their heads such that the two front head markers were positioned centered over the orbits of the skull. The spine and sacrum markers were fastened using medical tape to fix strong magnets over the specified vertebrae. The reflective markers were then attached using magnets outside of the athletic top to ensure the markers stayed centered over the intended vertebrae despite movements of the shirt during performance trials. The two pelvic markers on the bilateral posterior superior iliac spines (PSIS) were fixed using adhesive stickers on the exterior of the clothing. Table 7.1 presents a full list of the location of anatomical landmarks. Participants were permitted to warm up for five minutes prior to data collection. Participants could play anything they wished during this time, but many chose to warm up by reviewing the prescribed musical tasks.

Figure 7.2

Placement of Anatomical Markers

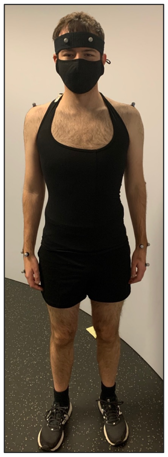



Table 7.1

Anatomical Landmarks for Placement of Reflective Markers

Region	Anatomical landmarks
Head	Four markers on head band: (Two anterior skull, two posterior skull)
Spinal vertebrae	C7 T3 T7 T11 L3 Sacrum
Pelvis (bilateral)	PSIS
Arms (bilateral)	Acromion Lateral epicondyle of the humerus Styloid process of the distal ulna Styloid process of the distal radius Distal aspect of the third phalanx (just proximal to the metacarpal phalangeal joint of the third digit)

7.2.4 Musical Tasks

Pianists performed a battery of 10 bi-manual musical tasks chosen to explore a variety of symmetrical and parallel arm movements patterns. Many of the tasks were based on common technical patterns such as scales. Some tasks required similar movements in each hand, while others required the hands to play dissimilar patterns simultaneously. The tasks were constructed to require varying degrees of hand displacement in the x- (horizontal) and y- (forward and backward) axes of the piano keyboard. Only a sub-set of the musical tasks are discussed in the results of this study, including: (1) parallel C major scales; (2) contrary motion C major scales; (3) two-note slurs; (4) chromatic 5-finger passages in the right and left hand (taken from exercises 12a and 12b of Bartók's *Mikrokosmos, Volume II* (Bartók, 1987/1940); (5) parallel and symmetric blocked 5ths (taken from exercises 17a and 17b of Bartók's *Mikrokosmos, Volume II* (Bartók, 1987/1940); and (6) a blocked octave whole-tone scale. Notation and playing descriptions of these tasks appear in the results section. The music notation and playing instructions for the full battery of playing tasks can be found in Appendix A of article four of this thesis.

7.2.5 Data Preparation

A detailed discussion of the analysis of the measured data can be found in article four of this thesis. In summary, the data was analysed using MATLAB™ by first synchronizing the time base of the Motion Capture and MIDI measurement systems using the depression of the low A (MIDI note 21) and a marker attached to it. The MIDI data was matched to the expected pattern of notes in each task allowing us to identify playing errors of various types as well as the start and end times for each task. The data was aligned to a right-handed coordinate system with the x axis parallel to the line connecting the fixed markers on the front edge of the keyboard and a vertical z axis. The data was examined by creating three dimensional plots of the positions of each marker before performing detailed principal component analysis.

7.3 Analysis

PCAs were conducted on all motion trajectories from each task (PCA^{all}). Separate PCA^{all} were conducted for each trial, of each task, for each participant. We then conducted three separate PCAs on subsets of the motion capture data of each trial, divided into three independent groups: (1) right arm (PCA^{right}); (2) left arm (PCA^{left}); and (3) torso (PCA^{torso}). Markers included in each of the subgroups are listed in table 7.2. The data were mean-centered and normalized (the mean of each variable was subtracted from the data points of the corresponding variable and divided by the standard deviation) prior to conducting PCA. The data was not filtered because we did not want to remove variation in the data which may contain information related to task-determined or participant-determined characteristics. Since analysis was conducted on position data only, and not on secondary variables calculated from position, such as velocity, angles, or acceleration, any measurement error arising from the motion capture system would not be amplified from additional computations.

Table 7.2

Anatomical Markers Included in PCA Subgroups

Subgroup	Markers Included
Torso	Head markers (x4 on headband. two anterior skull, two posterior skull)
	C7
	T3
	T7
	T11
	L3
	Sacrum
	Left PSIS (posterior superior iliac spine)
	Right PSIS
Arm (right and left are separate functional groups)	Acromion
	Lateral epicondyle of the humerus
	Styloid process of the ulna
	Styloid process of the radius
	Distal aspect of the third phalanx (just proximal to the metacarpal phalangeal joint of the third digit)

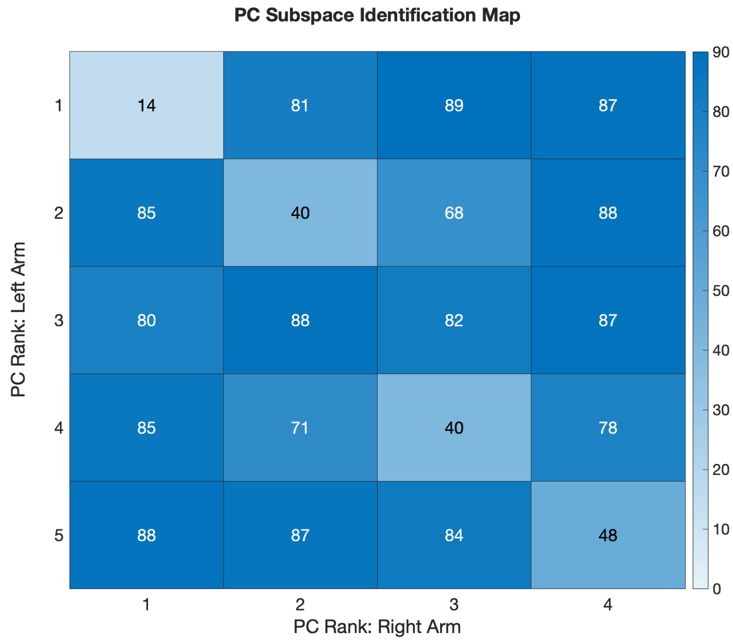
An original MATLAB™ code plotted all PC waveforms for PCs greater than or equal to two percent of the overall variance for each of the four groups. A PC waveform plots the values contained in the score vectors generated by the PCA in MATLAB™. PC waveforms in this paper are not data reconstructions but plots of the PC vectors. We chose a two-percent threshold of inclusion to limit the number of PCs to be compared and because it is difficult to distinguish whether the variance described by very small PCs results from performers' movements or random noise introduced by the environment or equipment. For a given task, trial, and participant, the PC waveforms from all trajectories were plotted next to the waveforms from the torso, left arm, and right arm to permit visual comparisons of the overall shape and frequency content.

MATLAB™ was used to objectively quantify the degree of similarity between pairs of PCs by calculating the angle between them. The software did pairwise comparisons of sets of individual PC vectors by calculating the inverse cosine of the absolute value of the dot product of the two normalized principal components. This results in an angle which we refer to as an inter-PC angle, reported in degrees, that can range from 0 to 90 degrees. The inter-PC angles were displayed in a grid allowing for the angles between all possible pairs of PCs from the PCA of two data sets. These grid systems, referred to as PC subspace identification maps, highlight smaller angles in lighter colours and larger angles in darker colours. Smaller angles between two PCs mean that they are closer to being the same vector. Larger angles between the two PCs mean they are more independent. We interpret the size of each angle relative to the other angles in a particular comparison. Typically, an angle of less than 20 degrees was noted between visually similar PCs while angles greater than 60 degrees generally resulted from comparing PCs that are visually distinct. This paper focuses on cases where low inter-PC angles were clearly identifiable.

Figure 7.3 shows an example of a PC subspace identification map comparing PCs from participant 4's right and left arm PCAs during the performance of contrary scales. Each row of the grid system corresponds to a PC in the left arm. Each column corresponds to a PC in the right arm. The square at the intersection of a pair of PCs (one from the left arm and one from the right arm) contains the inter-PC angle between the two PC vectors. For example, the light-coloured square in the upper left-hand corner indicates that $PC1^{left}$ and $PC1^{right}$ are separated by an inter-PC angle of 14 degrees. This is an example of a very strong subspace relationship because the inter-PC angle is very low. The low inter-PC angle suggests that the variation represented by PC1 in both arms is very similar. The light coloured square two boxes in from the left and down two boxes down from the top shows that $PC2^{left}$ and $PC2^{right}$ are separated by a low inter-PC angle of 40 degrees. Even though this inter-PC angle is higher than the previous one, it is uniquely low among other PC pairs involving either $PC2^{left}$ or $PC2^{right}$ and indicates a relationship between the two PCs. The third row, corresponding to $PC3^{left}$ has only dark coloured boxes representing high inter-PC angles ranging from 80 to 88 degrees. The absence of low inter-PC angles in this row indicates that $PC3^{left}$ does not share any subspace relationships with any PCs in the right arm. This suggests that $PC3^{left}$ represents variation unique to the left arm which is not found in the right arm data.

Figure 7.3

Example of a PC Subspace Identification Map Comparing Left and Right Arm PCs: Participant 4, Contrary Scales, Trial 1

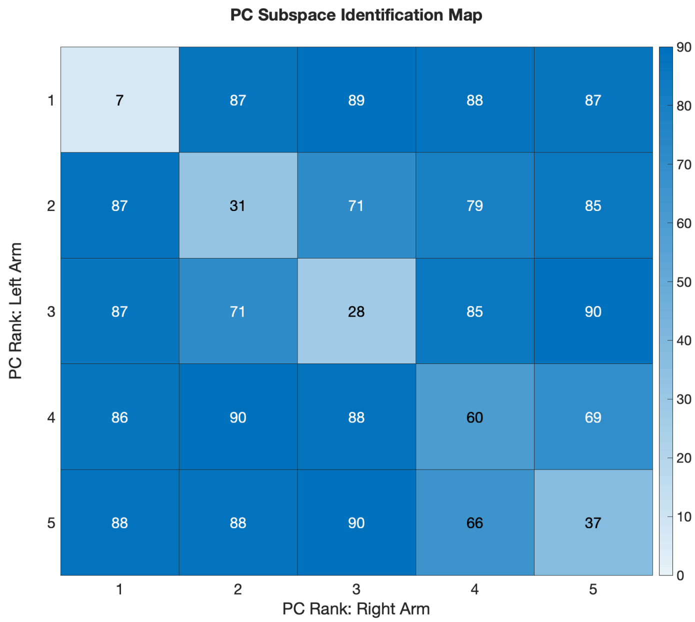


Note. Numbers in the squares are inter-PC angles, measured in degrees, between 0° and 90°. Lighter coloured squares correspond to lower angles. Darker coloured squares correspond to higher angles.

The primary researcher examined three hundred of the nine-hundred total PC subspace identification maps from various participants and musical tasks to locate instances of low inter-PC angles. For an inter-PC angle to be considered low it had to be the lowest angle in the column and the row of the subspace identification map and there could be no other angle within 10 degrees of the lowest angle in the column or the row. The existence of low inter-PC angles were then cross referenced with plots of the PCs from all the data, just the torso, just the right arm, and just the left arm to see if PCs sharing a low inter-PC angle appeared visually similar. Our observations suggest that PCs consistently retained a level of visual similarity for angles 50 degrees or lower, however, the size of the angle suggesting the presence of a subspace relationship depended on the ranking of the PC. We observed that subspaces between pairs in which one or both PCs were ranked higher than three (PCs explain less of the overall variance the higher their ranking number) were likely to have inter-PC angles in the range of 30-45 degrees. PC pairs between PCs ranked lower than three tended to have smaller inter-PC angles. Due to the variation among these inter-PC angles, it was not possible to identify an absolute range of angles indicating strong subspace relationships that would be suitable for all tasks and all PC ranks. Therefore, the decision to consider an inter-PC angle as indicative of a possible subspace relationship depended on whether the angle was uniquely low among all subspace pairs involving the PCs in the pair. For example, in the sample PC subspace identification map presented in figure 7.4, row four, corresponding to $PC4^{left}$ has three large inter-PC angles ranging from 86 to 90 degrees relating it to PCs 1, 2, and 3 of the right arm. However, the inter-PC angles between $PC4^{left}$ and PCs 4^{right} and 5^{right} are similar, at 60 and 69 degrees, respectively. In this case, no subspace will be identified between $PC4^{left}$ and the right arm, since there are no uniquely low angles comparing $PC4^{left}$ to any PCs in the right arm. The interpretation of the angle magnitude is further complicated by the variance in the data generated by required aspects of the tasks.

Figure 7.4

Example of a PC Subspace Identification Map Comparing Left and Right Arm PCs: Participant 2, Contrary Scales, Trial 1



7.4 Results

In our previous work (Beacon, Russell, Comeau, 2023b) visual inspection yielded many examples of distinctly shaped PC waveforms visible in both the PCA^{all} and one or more $PCA^{subgroups}$ that suggested the presence of invariant one-dimensional PC subspaces. Drawing from our previously established framework of variation in musical performance, we sought to determine if the mathematical approach of functional subspace identification based on computing inter-PC angles could quantitatively identify PC subspaces related to both task-determined and participant-determined variation in the motion capture data (Beacon, Russell and Comeau, 2023b). The constraints predetermined by the structure of the musical tasks selected for our current study presented opportunities to test the ability of functional subspace identification to help identify task-specific and participant-specific subspaces by drawing connections between subspace characteristics and known coordination characteristics expected based on task parameters. We present the results of this investigation in two parts: Part one presents examples of task-specific subspaces that arise from properties of the tasks themselves; Part two explores examples of participant-specific subspaces that present evidence of pianists' unique coordination characteristics.

In the results, references to individual PCs by their ranked number will appear in an abbreviated form with reference to the PCA it was derived from in a superscript. For example, *principal component 1 from the right arm PCA* will appear as $PC1^{right}$. Occasionally the percentage of variance described by the PCA will be included in brackets after the PC as follows: $PC1^{right}$ (33.0%). Functional subspace identification requires comparing PCs in pairs. When the angle between two PCs is sufficiently low to suggest the presence of a subspace, the pair will be recorded in the following manner, followed by the inter-PC angle in square brackets: $PC1^{all} \approx PC1^{right}$ [17 degrees].

7.4.1 Results Part I: Influence of Task Constraints on One-Dimensional Subspaces

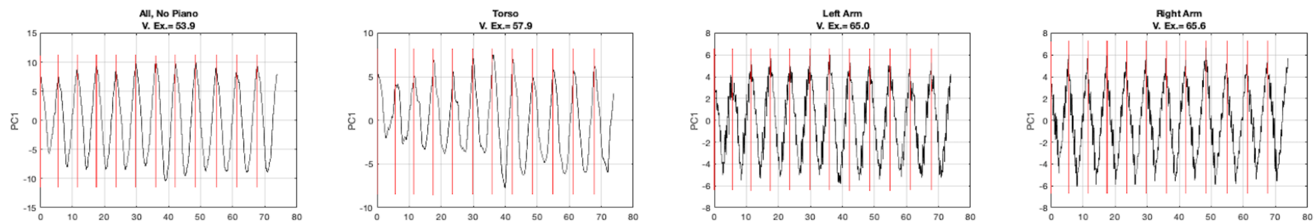
The first part of the results section presents examples of how the process of functional subspace identification can be used to identify task-dependent subspace characteristics in pianists' motion capture data. We first present examples from musical tasks requiring significant x-axis displacement of the hands (horizontally with respect to the keyboard). This is followed by examples from a symmetrical task requiring no horizontal displacement of the hands (two-note slurs) and a task requiring the hands play different musical patterns at the same time (chromatic five-finger passages). These examples were chosen since their task parameters have clear implications for coordination characteristics related to the independence of the torso and arms and expected symmetries between the two hands that we demonstrate can be identified using functional subspace identification. These predetermined task features can be used to test the ability of pc subspace identification to identify subspaces by determining if the subspace characteristics reflect known coordination features dictated by the musical task.

7.4.1.1 Examples of Task-Determined Subspaces in Tasks with Repeated X-Axis Displacement. When beginning the process of functional subspace identification, we quickly found that the clearest and most common example of similar waveform shapes suggesting subspaces occurred across PC1 of each of the four $PCA^{subgroups}$: PCA^{all}, PCA^{torso}, PCA^{left} and PCA^{right}. For example, figure 7.5 illustrates representative examples of PC1 waveforms for PCA^{all} and each $PCA^{subgroup}$ for musical tasks that required the arms to travel up and down the x-axis (horizontally with respect to the piano keys), resulting in repeated x-axis displacement of the hands. These tasks included: (A) parallel scales; (B) contrary scales; (C) five-finger pattern; and (D) blocked octaves (figure 7.6). Note that the horizontal axis of all PC waveform plots in this paper is time, measured in seconds, with time zero corresponding to the beginning of the first note of the task. The similarity of PC1 across all four PCAs for each of these four tasks arises due to the pervasiveness of the horizontal movement along the keyboard defined by the task parameters. Since PCs are ranked in ascending numerical order according to what percentage of the overall variance they explain, PC1 always accounts for the greatest proportion of the overall variance in the data set. Table 7.3 notes that on average, PC1 accounts for between 48.0% and 71.5% of the total variance of the data for these four tasks. The fact that the PC accounting for the greatest amount of overall variation in the data resembles the task parameters for the torso and arm subgroups indicates that the entire body coordinates to execute task parameters related to traversing the keyboard along the x-axis. This results in a pervasive, repetitive pattern in PC1 that mimics linear pathways and direction changes occurring in the musical notation of the musical scores corresponding to each task. The linear ascending and descending patterns pictured in figure 7.5 are not only common to all tasks that require the hands to perform a sequential figure repeatedly in ascending and descending direction, but to the coordination patterns of all pianists who execute these task parameters. This variation characteristics is pre-determined by the task and does not offer insight into unique coordination characteristics related to individual pianists' movement choices. However, this known variation pattern allows us to test the ability of functional subspace identification to find invariant subspaces between subgroups where we would expect to find them.

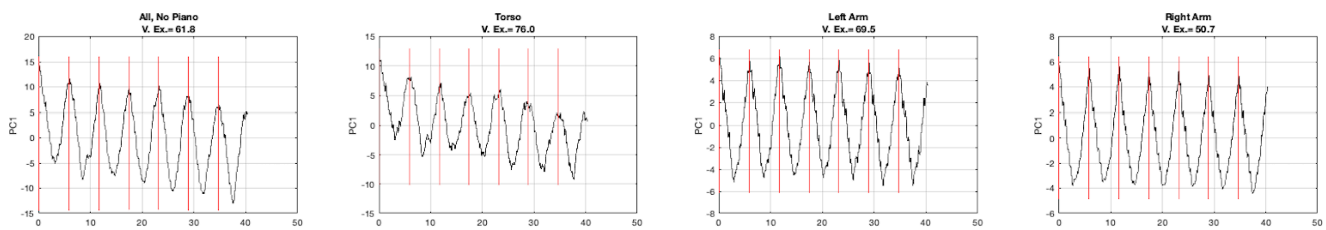
Figure 7.5

PC1 Waveforms for PCA^{all}, PCA^{torso}, PCA^{left} and PCA^{right} for Selected Musical Tasks

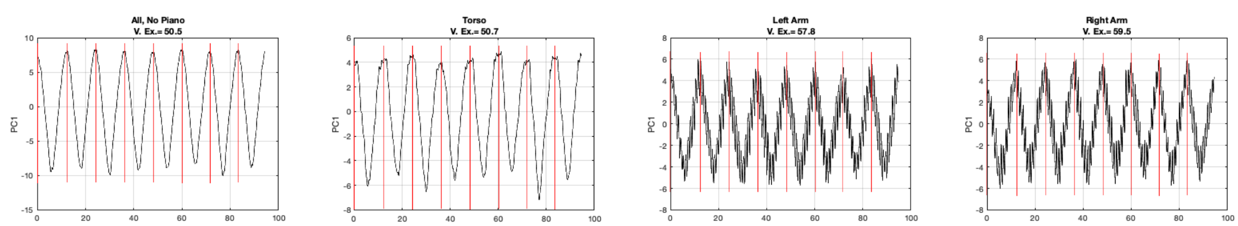
A) Parallel Scales, Participant 1, Trial 1:



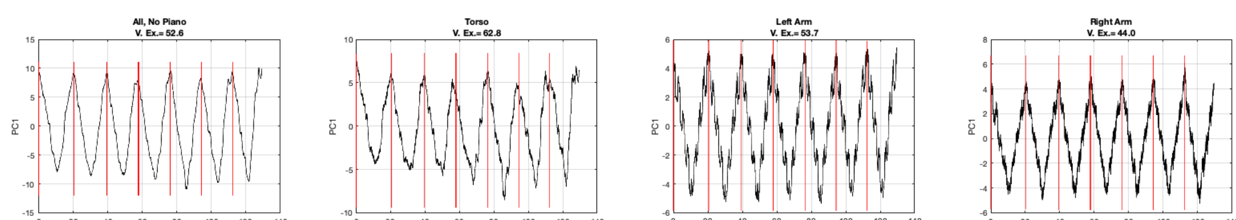
B) Contrary Scales, Participant 3, Trial 1:



C) Five-Finger Pattern, Participant 4, Trial 1:



Blocked Octaves, Participant 5, Trial 1



Note. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

Figure 7.6

Notation of Musical Tasks Involving Horizontal Hand Displacement

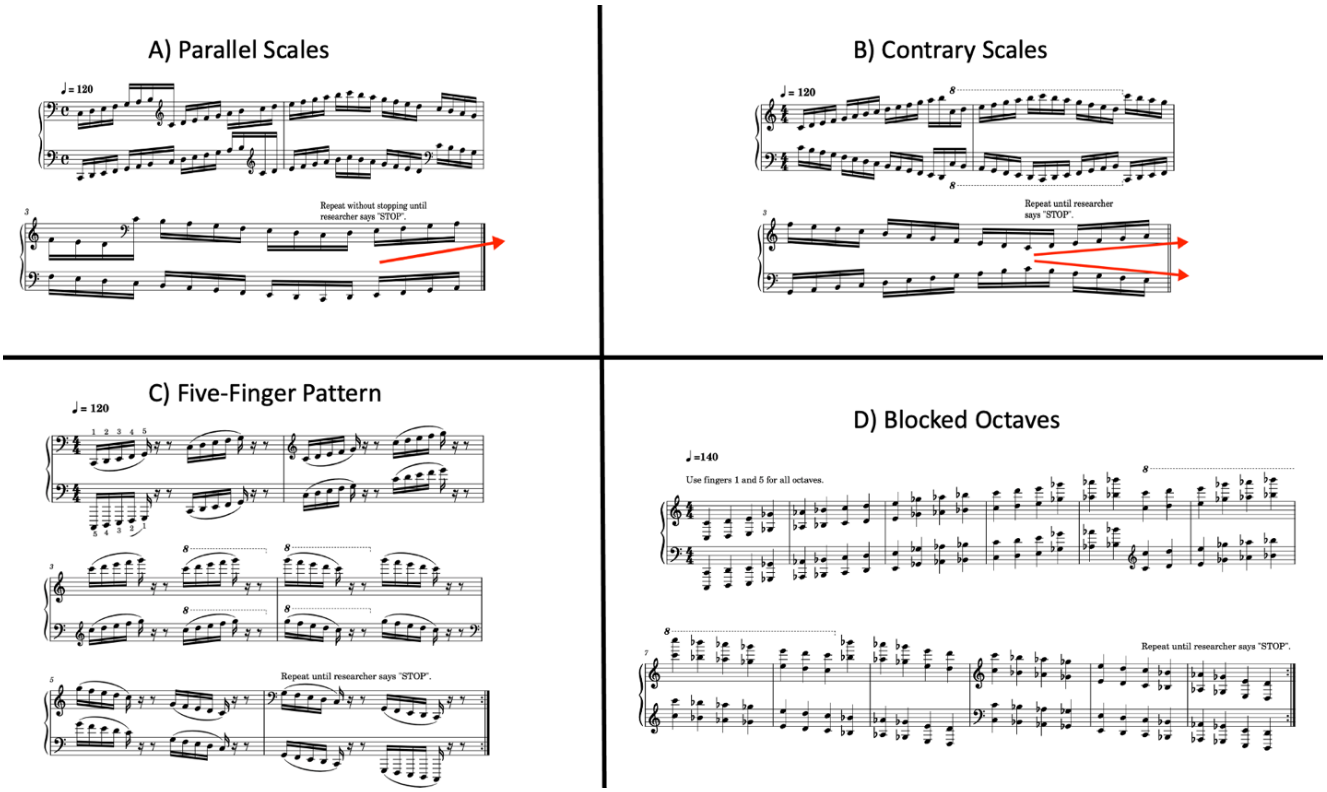


Table 7.3

Average Variance Explained by PC1 Across for Participants (Excluding Participant 5) and Trials for Tasks with X-Axis Displacement

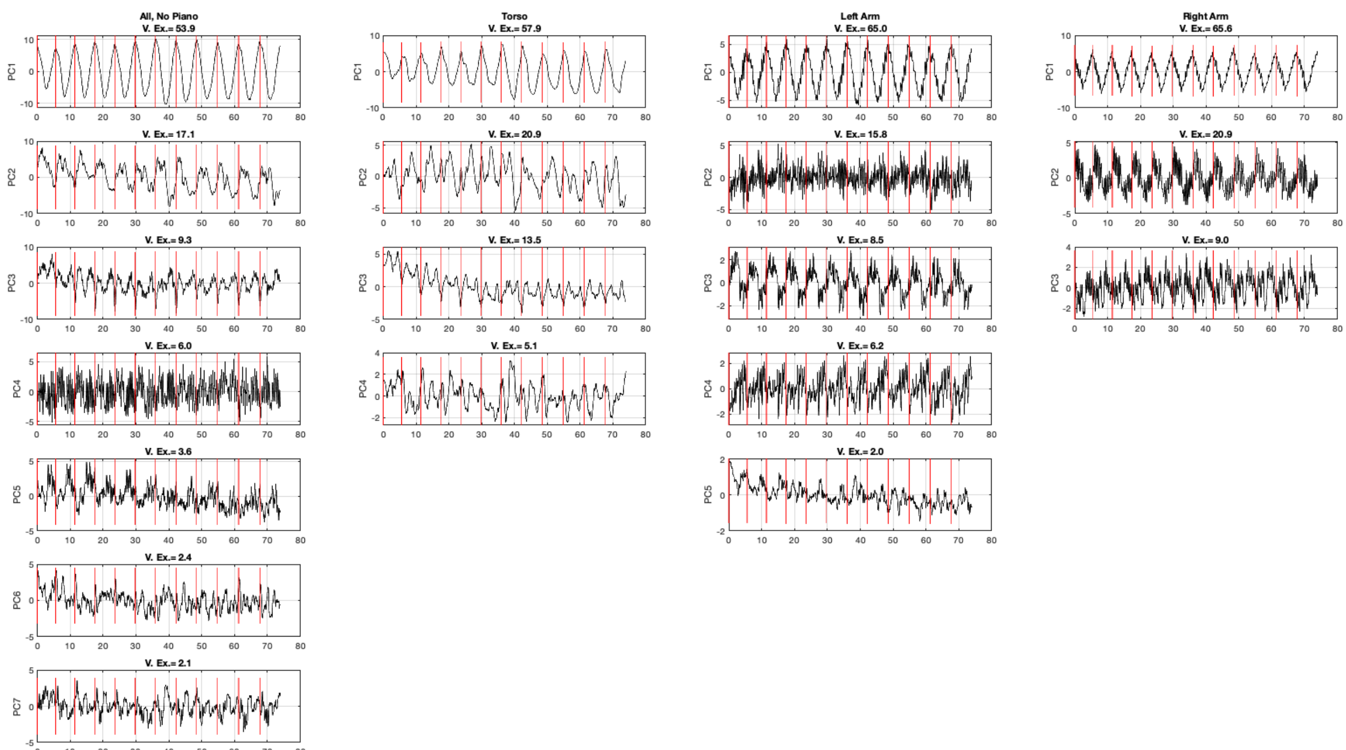
	Average Variance Explained by PC1 (%)			
Task	PCA All Data	PCA Torso	PCA Left Arm	PCA Right Arm
Parallel Scales	55.5	57.5	63.4	64.8
Contrary Scales	53.0	71.5	56.5	52.6
Five-Finger Pattern	53.6	53.1	66.1	62.9
Blocked Octaves	50.5	55.9	58.6	48.0

Note. Participant 5 was excluded due to missing data from one of the head markers.

The dominance of this alternating pattern is most visible in PC1 of each subgroup, but it can also be visually identified in shapes of PC waveforms of many of the smaller PCs. For example, figure 7.7 depicts the PC waveforms of each subgroup for participant 1's performance of parallel scales in trial 1. The notation of the parallel scale task appears in the upper-left quadrant of figure 7.6. The beginning of each new repetition of the task is marked with a vertical red line. It is evident from visual inspection that each PC contains the artefact of this ascending and descending pattern most clearly visible in PC1. The pervasiveness of this pattern may mask possible features in the shape and frequency content of the waveforms that may pertain to participant-specific coordination characteristics.

Figure 7.7

PCs $\geq$2% for Participant 1's Performance of Parallel Scales, Trial 1



Note. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

7.4.1.2 Examples of Task-Determined Subspaces in a Symmetrical Task with Minimal X-Axis Hand Displacement: Two-Note Slurs. PC1 was not always similar across all PCAs, especially for tasks that did not require extensive displacement of the hands and arms in the x-axis, including: (1) two-note slurs; (2) parallel 5ths (Bartók 17a); and (3) symmetric 5ths (Bartók 17b). For these exercises, the hands moved predominantly in the y-axis (forward and backward along the length of the key) and in the z-axis (up and down with respect to the floor and ceiling). Horizontal movement along the x-axis was restricted to a narrow range of keys positioned directly in front of the pianists' arms. Since these tasks do not require horizontal movement to the upper and lower extremes of the keyboard, the torso and head remain near the centre of the keyboard. However, the task does not impose specific constraints on the movement of the head and torso movements in the y- and z-axes. The pianist may choose to hold the torso still, providing a support for the arms, which are free to move. Contrastingly, they may choose to use the movement of their torso and spine to help carry the arms forward and backward (y-axis). Since the arms are free to move independently of the torso for this group of tasks, the PCs from the arms tend to be shaped differently than the PCs of the torso.

An example of the independence of the arms and torso can be seen in PC waveforms from performances of the two-note slurs task. Notation for the two-note slur task appears in figure 7.8. In this task, the right and left hands perform a synchronized, symmetrical sequence of notes in which pianists smoothly connect pairs of notes, releasing the keys of the second notes of the pair completely to introduce a short gap in the sound prior to continuing with the next connected pair.

Figure 7.8

Musical Notation for the Two-Note Slur Task

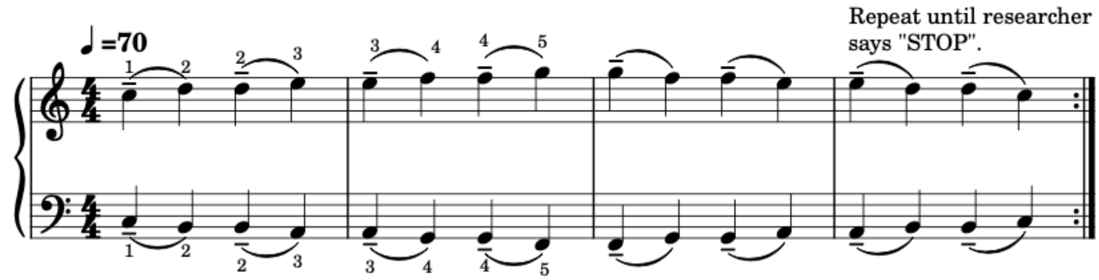
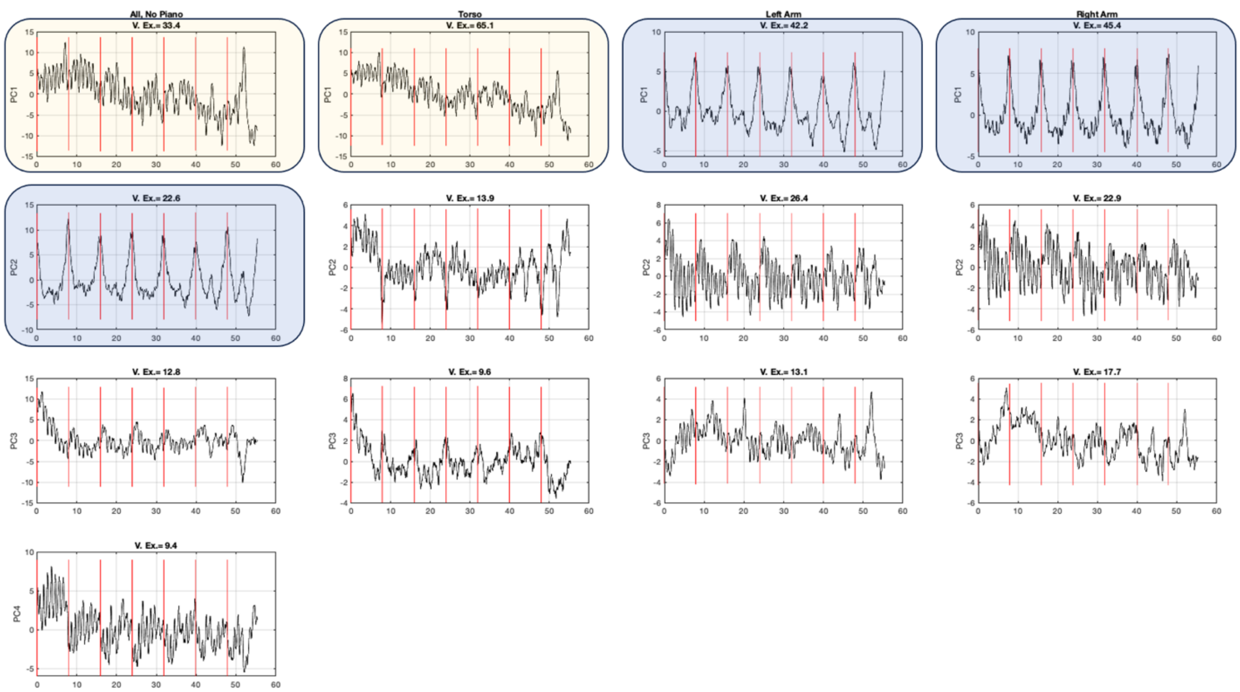


Figure 7.9 displays PC waveforms from the two-note slur performance of participant 2, trial 1. The yellow-coloured blocks in figure 7.9 highlight how the shape of PC1^{all} (33.4%) strongly resembles $\text{PC1}^{\text{torso}}$ (65.1%). The corresponding PC subspace identification map in figure 7.10 displays a low inter-PC angle between PC1^{all} and $\text{PC1}^{\text{torso}}$ [16 degrees], indicating that they represent similar vectors in their respective data sets. The blue-coloured blocks in figure 7.9 highlight that PC2^{all} (22.6%) resembles PC1^{left} and $\text{PC1}^{\text{right}}$. The similarity of $\text{PC1}^{\text{all,}}$ PC1^{left}, and $\text{PC1}^{\text{right}}$ is confirmed by the small angles between them displayed in figure 7.10: $\text{PC2}^{\text{all}} \approx \text{PC1}^{\text{left}}$ [15 degrees] and $\text{PC2}^{\text{all}} \approx \text{PC1}^{\text{right}}$ [18 degrees].

The distinct PC waveform appearing in PC2^{all}, PC1^{left} and $\text{PC1}^{\text{right}}$ indicates that an invariant, one-dimensional subspace exists within the larger data set that can almost entirely be explained by variation in the arm data alone, without including data of the torso. Similarly, the distinct PC waveform appearing in PC1^{all} and $\text{PC1}^{\text{torso}}$ indicates the presence of an invariant, one-dimensional subspace that can almost entirely be described by variation in the torso markers, without incorporating the arm markers. The fact that these patterns can be described by independent PCs in PCA^{all} suggests that in this task, the arms and torso movements can be described as independent sub-systems within the larger data set. In this case, the greatest percentage of overall variance in participant 2's performance of two-note slurs was described by a torso-specific pattern found in PC1^{all} (33.4%). The arm-specific pattern represented by PC2^{all} was also prevalent but accounted for a lower percentage of the overall variance (22.6%).

Figure 7.9

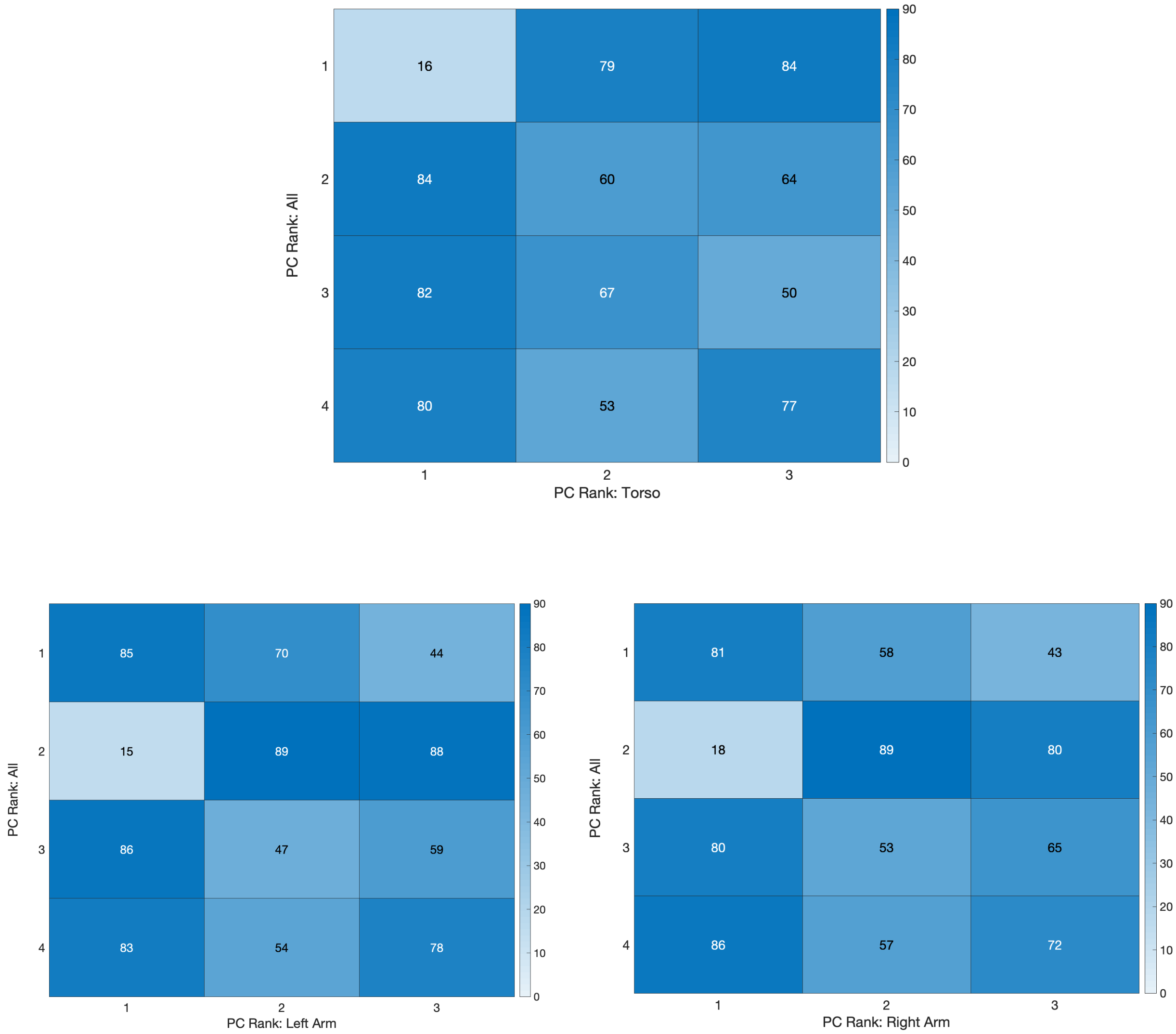
PC Waveforms ≥ 8% Variance from Two-Note Slurs, Participant 2, Trial 1



Note. Yellow-coloured blocks highlight PC subspaces between PCA^{all} and PCA^{torso}. Blue-coloured blocks highlight PC subspaces between PCA^{all} and PCA^{arms}. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

Figure 7.10

PC Subspace Identification Maps for PCs ≥8% from Two-Note Slurs, Participant 2, Trial 1



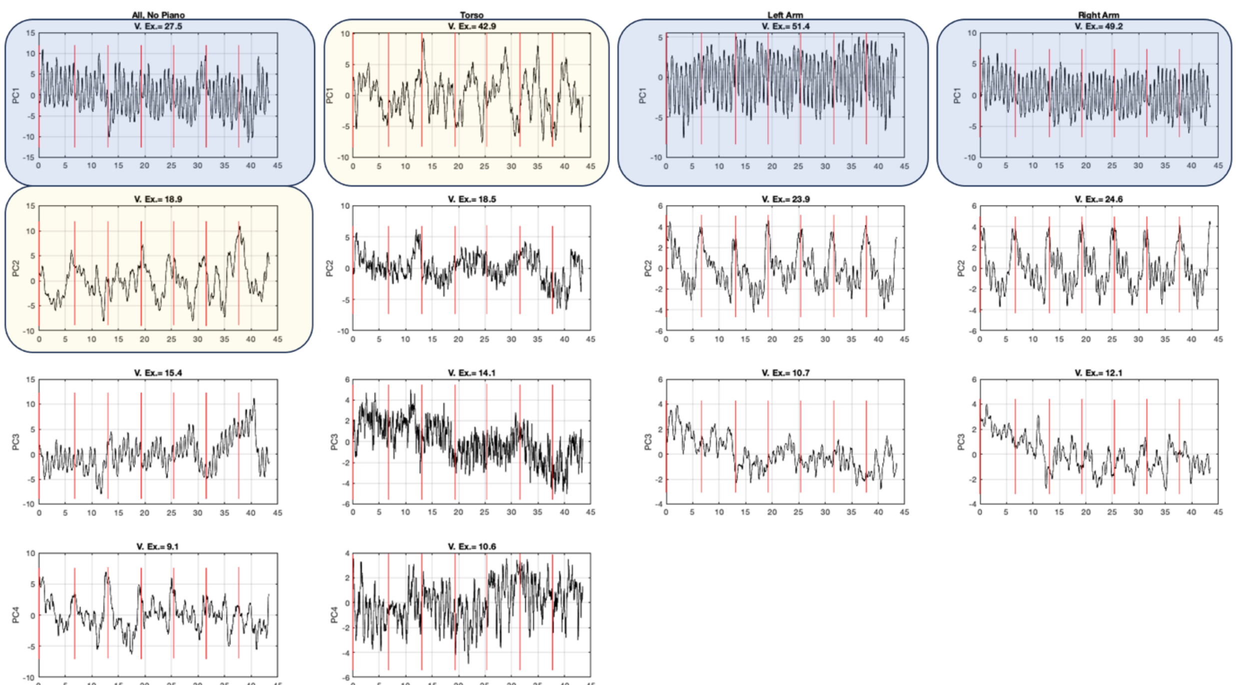
Note. Top, middle: torso-all comparisons. Bottom left: left arm-all comparisons. Bottom right: right arm-all comparisons.

The PC waveforms of other participants' performances of two-note slurs displayed similar independence between the largest arm-only PCs and largest torso-only PCs, suggesting that the task parameters permitted independent movement of the torso and arms. However, the distribution of variance between the arm-specific PCs and the torso-specific PCs varied depending on the participant. For example, for participant 3, $PC1^{all}$ (27.8%) strongly resembled both $PC1^{left}$ (51.4%) and $PC1^{right}$ (49.2%) in trial one, as highlighted by the blue-coloured blocks in figure 7.11. The corresponding PC subspace identification map in figure 7.12 confirms the similarity of these PCs, showing a relationship between $PC1^{all}$ and $PC1^{left}$ ($PC1^{all} \approx PC1^{left}$ [33 degrees]) and between $PC1^{all}$ and $PC1^{right}$ ($PC1^{all} \approx PC1^{right}$ [28 degrees]). The yellow-coloured blocks in figure 7.11 show that $PC2^{all}$ (18.9%) is most strongly related to $PC1^{torso}$ (42.9%) ($PC2^{all} \approx PC1^{torso}$ [41 degrees]). These PC relationships suggest that $PC1^{all}$, accounting for the greatest percentage of the overall variance in participant 3's performance, could be independently represented from the arm-only data. $PC2^{all}$, accounting for the second highest percentage of the overall variance, could be represented by torso-only data.

The process of functional subspace identification suggests that while arm movements dominated the variance in participant 3's performance, torso movements appeared to contribute more of the variance for participant 2. Comparing the different distributions of variance between torso-specific and arm-specific PCs across participants suggests that the degree to which arm-specific or torso-specific PCs contribute a greater proportion of the overall variance depends on the participant's unique coordination choices. However, the task parameters pre-determine a level of independence between the torso and arm movements that is consistent across all participants. This task-determined independence of torso and arm movements can be described by locating common waveforms between PCA^{all} and $PCA^{subgroups}$ using the inter-PC angles. These examples illustrate that it is possible to use functional subspace identification to identify task-dependent variation characteristics in the motion capture data of pianists, since the invariant subspaces identified reflect the expected independence and coordinative features expected between the functional subgroups based on the task parameters. It also illustrates that functional subspace identification can be used to highlight relationships between PCs in PCA^{all} and data specific to the anatomical markers included in functional $PCA^{subgroups}$.

Figure 7.11

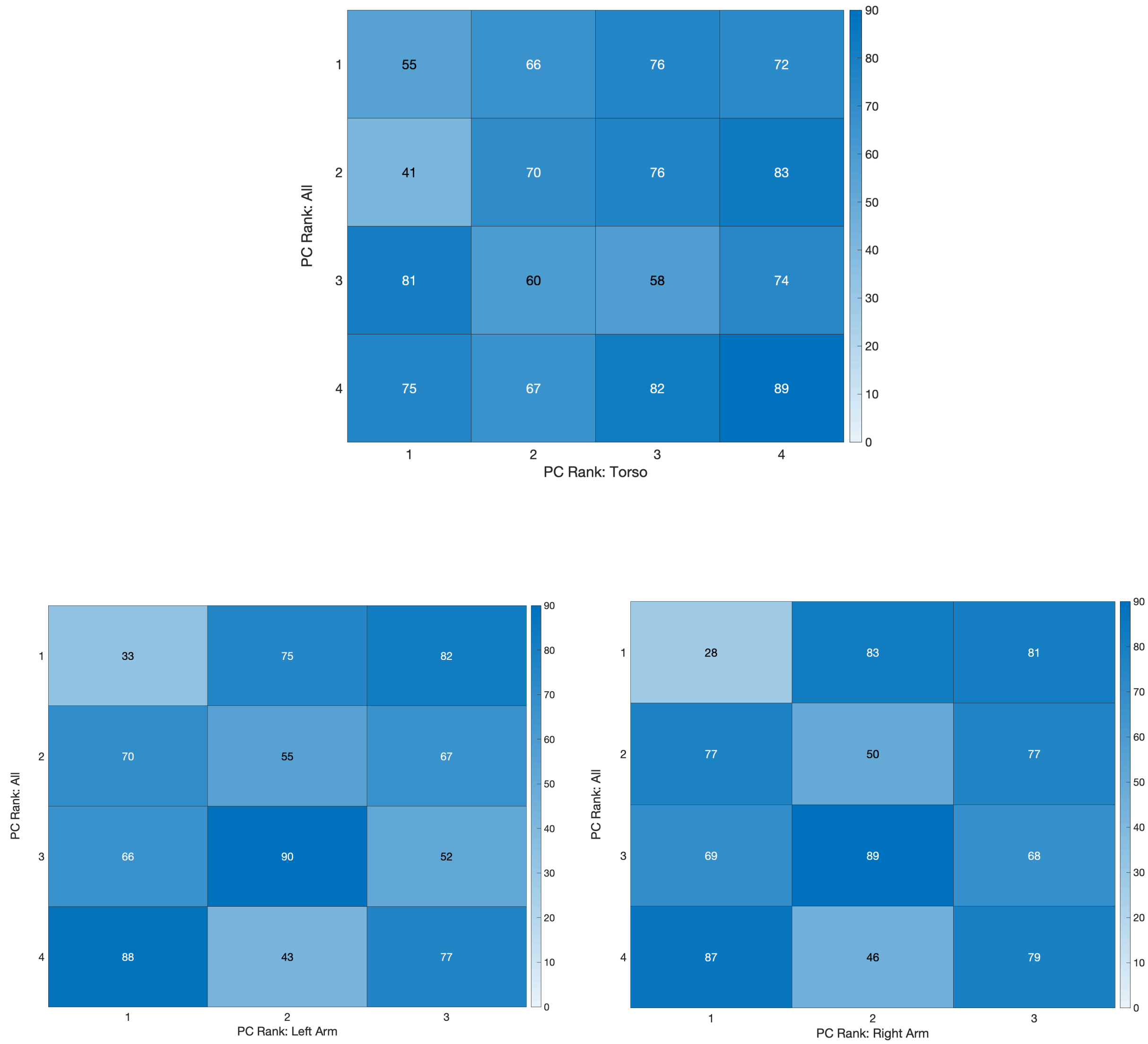
PC Waveforms ≥8% Variance from Two-Note Slurs, Participant 3, Trial 1



Note. Yellow-coloured blocks highlight PC subspaces between PCA^{all} and PCA^{torso}. Blue-coloured blocks highlight PC subspaces between PCA^{all} and PCA^{arms}. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

Figure 7.12

PC Subspace Identification Maps for PCs ≥ 8% from Two-Note Slurs, Participant 3, Trial 1

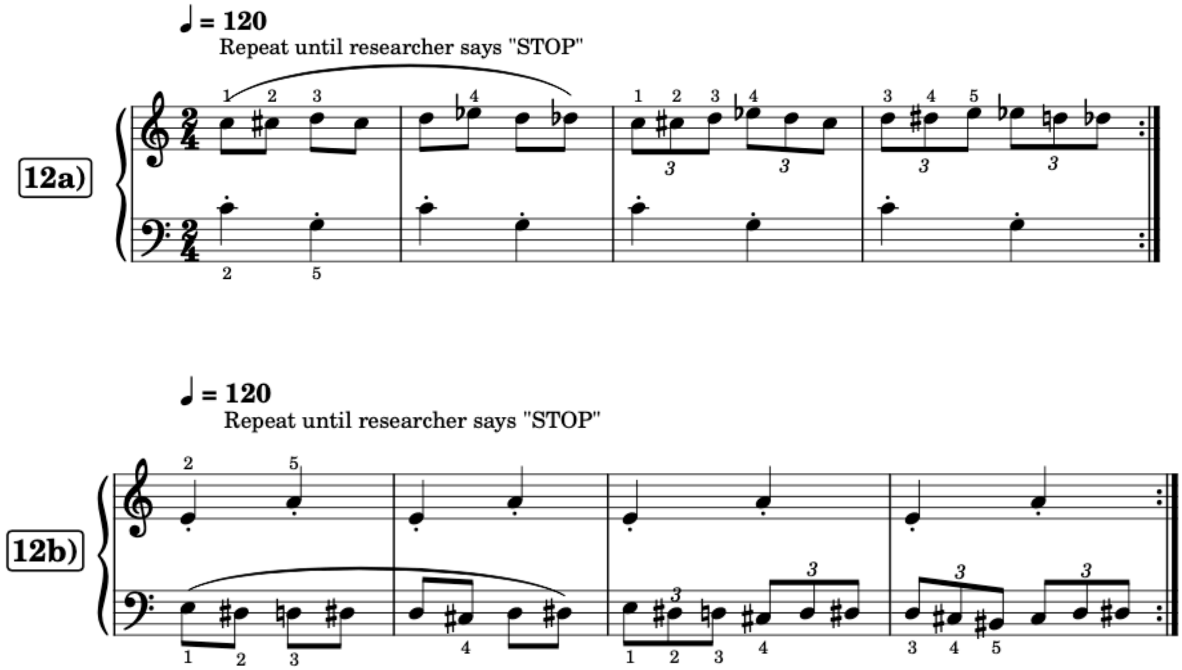


Note. Top, middle: torso-all comparisons. Bottom left: left arm-all comparisons. Bottom right: right arm-all comparisons.

7.4.1.3 Examples of Task-Determined Subspaces in a Task Requiring Different Musical Patterns in Each Hand: Chromatic Five-Finger Passages. Further evidence supporting the usefulness of PC subspaces for helping identify task-specific coordination characteristics comes from performances of the Bartók 12a exercise (chromatic five-finger passage for the right hand) and Bartók 12b exercise (chromatic five-finger passage for the LH.) Notation for these exercises appear in figure 7.13. In exercise 12a, the right hand performs a chromatic five-finger passage, playing neighbouring white and black keys half-step by half-step on the keyboard in duple and triplet eighths note subdivisions, while the left hand performs a steady ostinato of quarter notes alternating over the interval of a perfect fourth. Exercise 12b is composed symmetrically to 12a so that the right hand plays alternating quarter notes on the beat while the left hand performs a chromatic five-finger passage. The hands remain in the same position on the keyboard throughout the exercise, with minimal displacement in the x-axis. As in the case of the two-note slurs, the arms and torso are free to move independently. The right and left hands must also move independently of one another to each execute contrasting musical patterns in each hand. We hypothesized that the PC waveforms of the right and left arm PCAs should vary independently of one another since the right and left hands perform contrasting patterns simultaneously. If the invariant PC subspaces reflect this independence of the right and left arms for this task we will have more evidence that the PC subspace identification tool is functioning as expected.

Figure 7.13

Bartók Exercises 12a and 12b from Volume II, Mikrokosmos



Note. Source of musical score: Bartók, B. (1987). *Mikrokosmos: Volume II* [Musical score]. Hawkes & Son (London) Ltd. (Original work published 1940).

The PC waveforms from these two tasks exemplify how one-dimensional PC subspaces can be used as a tool to highlight task-related independent variation characteristics in the torso, right arm, and left arm PCAs. For example, figure 7.14 displays the PC waveforms accounting for greater than five percent variance from participant 4's performances of exercises 12a in trial 1 (a five percent threshold was used here to reduce the number of figures on the page for easier reading). Table 7.4 presents a summary of similar PC pairs occurring among the four PCAs (PCA^{all} and the three $PCA^{subgroups}$) from the same performance. The yellow-coloured blocks in figure 7.14 highlight that $PC1^{all} \approx PC1^{torso}$ [23 degrees] and $PC2^{all} \approx PC2^{torso}$ [26 degrees]. Together, $PC1^{all}$ and $PC2^{all}$ account for 61.2% of the overall variance in PCA^{all} and 85.8% in $PCA^{torso.}$ The presence of torso-specific subspaces in $PC1^{all}$ and $PC2^{all}$ suggests that for this participant, torso movement dominated the movement variation in the data set.

The blue-coloured blocks in figure 7.14 highlight subspace relationships between PCA^{all} and PCA^{left}. The corresponding PC subspace pairs are found in the left arm column of table 7.4. $PC1^{all}$ and $PC2^{all}$ appear to relate to $PC3^{left}$ and $PC2^{left}$, respectively, based on the low angles inter-PC angles between the pairs: $PC1^{all} \approx PC3^{left}$ [32 degrees] and $PC2^{all} \approx PC2^{left}$ [35 degrees]. However, the strongest relationship between PCA^{all} and PCA^{left} occurs in the pair $PC3^{all} \approx PC1^{left}$ [23 degrees]. Since these two PCs only relate to each other and neither shares a similarly strong relationship with any other PC, we can identify the pattern they represent as an independent PC subspace relating to variation unique to the left arm that persists despite the inclusion of the other variables in PCA^{all}. It is not surprising that the left-arm would exhibit unique variation patterns for this task, since it requires the left and right arm to perform very different movements. The left-arm must execute short, vertical strokes with the hand and wrist to perform the staccato (detached) articulation. By contrast, the right hand must maintain contact with the keys to perform the legato (smooth) articulation, connecting the sound of each note to the next. This example demonstrates that PC subspace identification is functioning as expected to locate invariant PC subspaces where they should be based on task parameters.

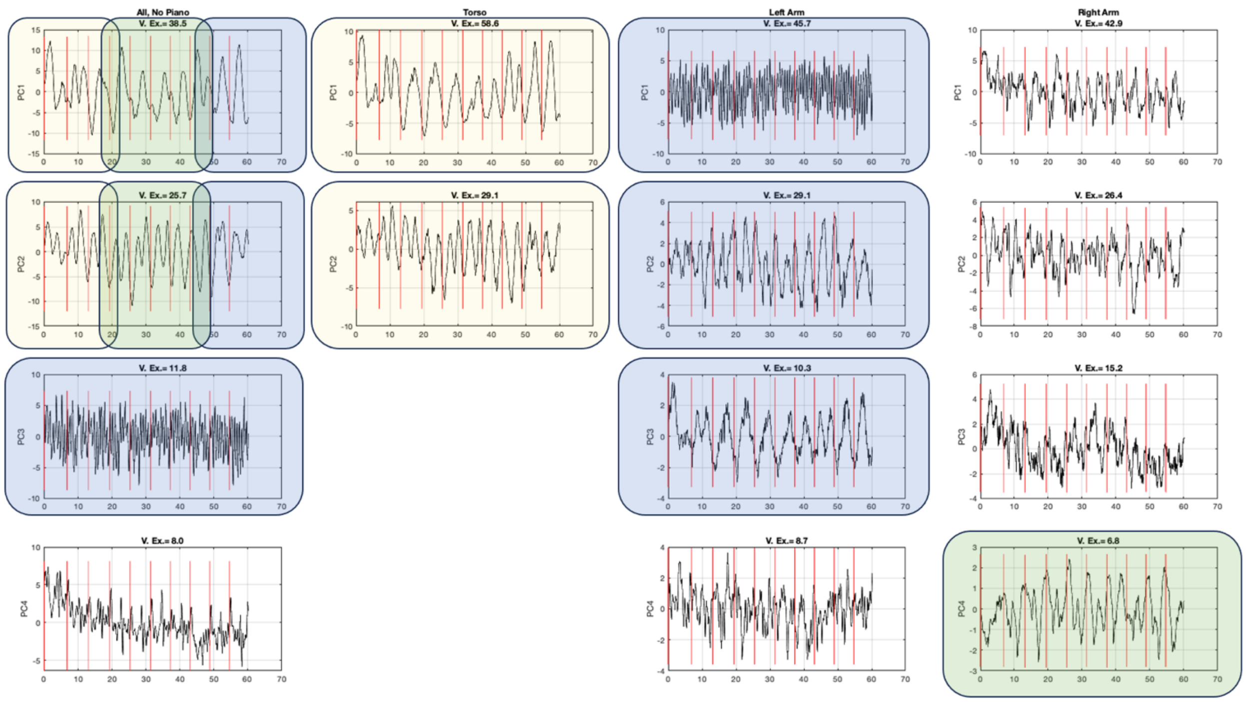
The only PC subspace pair between PCA^{all} and PCA^{right} appearing at the 2% variance threshold was $PC2^{all} \approx PC4^{right}$ [36 degrees], highlighted in the green rectangle in figure 7.15. We did not count the inter-PC angle of 47 degrees between $PC1^{all}$ and $PC1^{right}$ as evidence of a subspace because that angle was not uniquely low to the row and the column. Since $PC2^{all}$ has an even stronger relationship with $PC2^{torso}$ [27 degrees], it is likely that the variation represented by $PC4^{right}$ (6.8%) may be associated with torso movement. Interestingly, $PC1^{right}$, $PC2^{right}$ and $PC3^{right}$ did not have any pairwise relationships with any individual PCs greater than or equal to 2% variance PCs in PCA^{all}. The absence of right-hand specific subspaces in the larger PCs of PCA^{all} may have occurred because smooth execution of the chromatic scale requires mostly finger flexion movements with the possibility of adding minimal rotation of the forearm or flexion and extension of the wrists. There were no anatomical markers on the fingers to measure individual finger flexion, and the small movements of the hand and wrist may simply not be large enough to contribute a large proportion of variation to the complete data set.

We hypothesized that $PC5^{right}$ and $PC6^{right}$ may form subspace pairs with smaller PCs from PCA^{all}. To investigate this further, we compiled the PC subspace identification map of all PCs greater than or equal to 0.5%. The red rectangles in figure 7.15 show that reducing the variance threshold to 0.5% reveals two new subspaces between PCA^{all} and PCA^{right}: $PC8^{all} \approx PC5^{right}$ [48 degrees] and $PC10^{all} \approx PC6^{right}$ [35 degrees]. We noted that $PC5^{right}$ did not share an inter-PC angle lower than 48 degrees with any other PC from PCA^{all}. Similarly, $PC6^{right}$ did not share an inter-PC angle lower than 35 degrees with any other PC from PCA^{all}. This suggests that $PC5^{right}$ and $PC6^{right}$ represent subspaces describing variation related to the right arm movement that is independent of the other data. As expected, although we were able to locate right-arm-specific subspaces, they appear to account for a much smaller percentage of the overall variance compared to the left-arm- and torso-specific subspaces. Finally, we noted that all inter-PC angles comparing PCs from the right and left arms were very high, with the lowest angle occurring between the pair $PC4^{right} \approx PC3^{left}$ [47 degrees] (black rectangle in figure 7.16). The absence of strong relationships between PCs in the right and left arms supports the hypothesis that the right arm and left arm mostly move independently of one another during the performance of this task, confirming that PC subspace identification identifies invariant PC subspaces where they should be based on task parameters.

Applying the process of functional subspace identification to participant 4's first trial of exercise 12a revealed that the torso and arms vary independently, and that the torso movements contribute the greatest proportion of the overall variation in the data set. It also revealed that the variance of the right and left arm was not strongly related, confirming that the right and left arms moved independently of one another for this task. Since left-arm subspaces occurred with larger PCs in PCA^{all} and accounted for a greater proportion of the overall variance, we can infer that for this task, the small right arm movements may be overshadowed by larger movements in the torso and left arm. Nonetheless, the appearance of a right-arm specific subspace associated with the smaller $PC8^{all}$ (1.5%) and $PC10^{all}$ (0.8%) suggests that even though they account for only a very small percentage of the overall variance, there are unique, right-arm specific patterns that exist independently within the full data set. In many other studies, smaller components are considered residual variation that may be too stochastic to contain meaningful patterns (Daffertshofer et al., 2004). However, this example suggests that important information relating to pianists' movements may be hidden in the smaller components of PCA subgroups that could be useful in identifying task-specific or participant-specific coordination patterns in piano playing.

Figure 7.14

PC Waveforms from Participant 4's Performance of Exercise 12a, Trial 1



Note. The chromatic passage is in the right hand for Bartók exercise 12a. Yellow = 'all' compared to 'torso'. Blue = 'all' compared to 'left arm', and green = 'all' compared to 'right arm'. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

Table 7.4

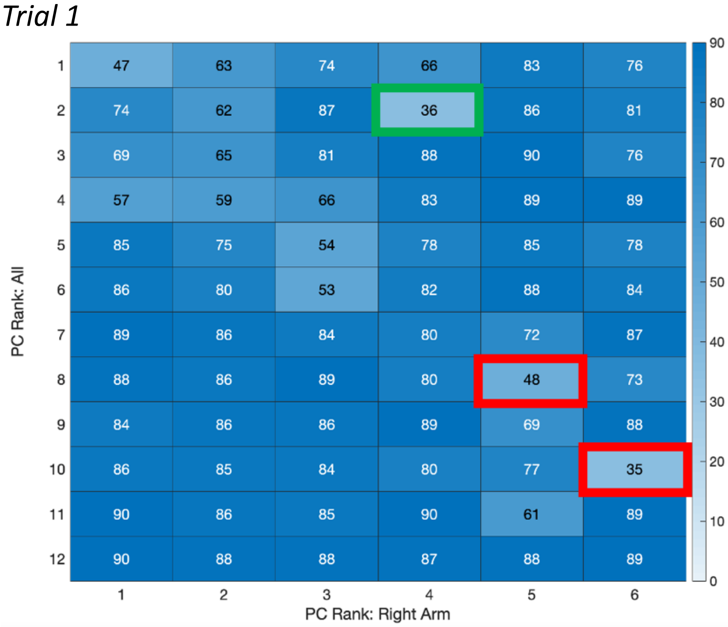
Summary of PC Similarity Pairs from Participant 4's Performance of Exercise 12a, Trial 1

	PC Similarity Pairs and Inter-PC Angles (°)		
PCA Subgroup	Torso	Left Arm	Right Arm
All	PC1 ≈ PC1 [23]	PC1 ≈ PC3 [32]	PC2 ≈ PC4 [36]
	PC2 ≈ PC2 [27]	PC2 ≈ PC2 [35]	*$PC8^{all}$ ≈ $PC5^{right}$ [48]
		PC3 ≈ PC1 [23]	*$PC10^{all}$ ≈ $PC6^{right}$ [35]

Note. The first PC in the pair is always from 'all'. Pairs with marked with * appear when the variance threshold is lowered to 0.5%.

Figure 7.15

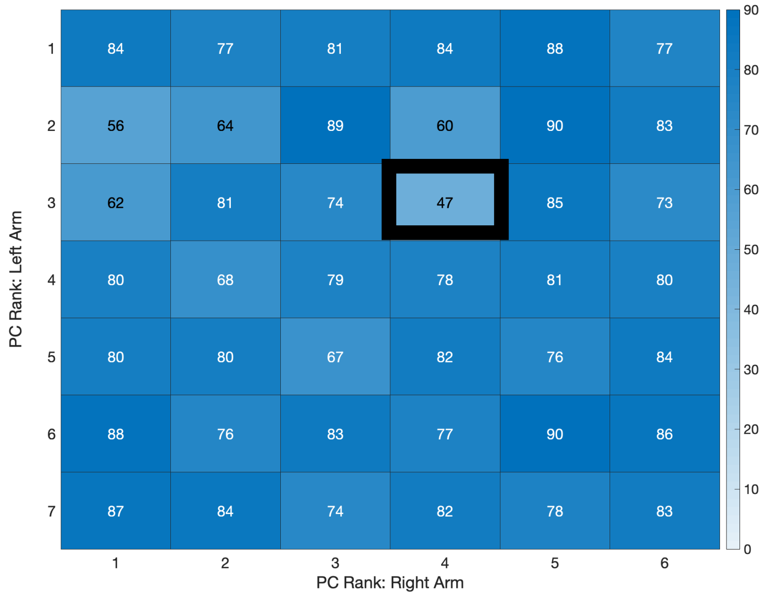
PC Subspace Identification Map for PCA^{all} and PCA^{right} (PCs ≥ 0.5%), Participant 4, Exercise 12a, Trial 1



Note. The green subspace appears at the 2% variance threshold. The red subspaces appear when the threshold is reduced to 0.5 %.

Figure 7.16

PC Subspace Identification Map for PCA^{left} and PCA^{right} (PCs $\geq$ 0.5%), Participant 4, Exercise 12a, Trial 1



Comparing participant 4's performance of exercise 12a with their performance of the musically symmetrical exercise 12b provides an opportunity to examine how the variation profile described by the PCs in each subgroup changes when the roles of the right and left hands are reversed. Figure 7.17 illustrates the PC waveforms from participant 4's performance of exercise 12b in trial 1. As in 12a, $PC1^{all}$ and $PC2^{all}$ from 12b strongly relate to $PC1^{torso}$ and $PC2^{torso}$: $PC1^{all} \approx PC1^{torso}$ [15 degrees] and $PC2^{all} \approx PC2^{torso}$ [21 degrees]. Together, $PC1^{all}$ and $PC2^{all}$ accounted for 67.5% of the overall variation in the data. This is very similar to the amount explained by $PC1^{all}$ and $PC2^{all}$ in exercise 12a (61.5%), suggesting that the torso movements contributed the greatest proportion of the overall variance in each task for this participant.

Table 7.5 summarizes subspace pairs between PCA^{all} and $PCA^{subgroups}$. For exercise 12b, $PC3^{all}$ related to two PCs in PCA^{right}: $PC3^{all} \approx PC1^{right}$ [46 degrees] and $PC3^{all} \approx PC2^{right}$ [50 degrees]. The waveform of $PC3^{all}$ is similar in shape and frequency content for both exercise 12a (figure 7.14) and 12b (figure 7.17), suggesting this PC waveform may relate to a similar aspect of the musical pattern in each task. The fact that $PC3^{all}$ is more strongly related to the right arm in exercise 12b likely arises because the right hand is now performing the pattern than the left hand performed previously. It should be noted that PCs derived from the same PCA are perpendicular to each other and the variance they represent is independent. This makes it difficult to interpret how both $PC1^{right}$ and $PC2^{right}$ can both relate to the same PC ($PC3^{all}$). It could be that $PC3^{all}$ contains variance related to two aspects of a musical pattern that are represented separately in the right arm movements. It may also be possible that the subspaces would be more clearly represented in a dimension higher than one. For the purposes of this investigation, it is enough to say that $PC3^{all}$ is clearly related to right arm PCs in exercise 12b instead of left arm PCs as it was in 12a, even if we are not able to precisely discern whether $PC1^{right}$ or $PC2^{right}$ is more strongly related using the inter-PC angle alone.

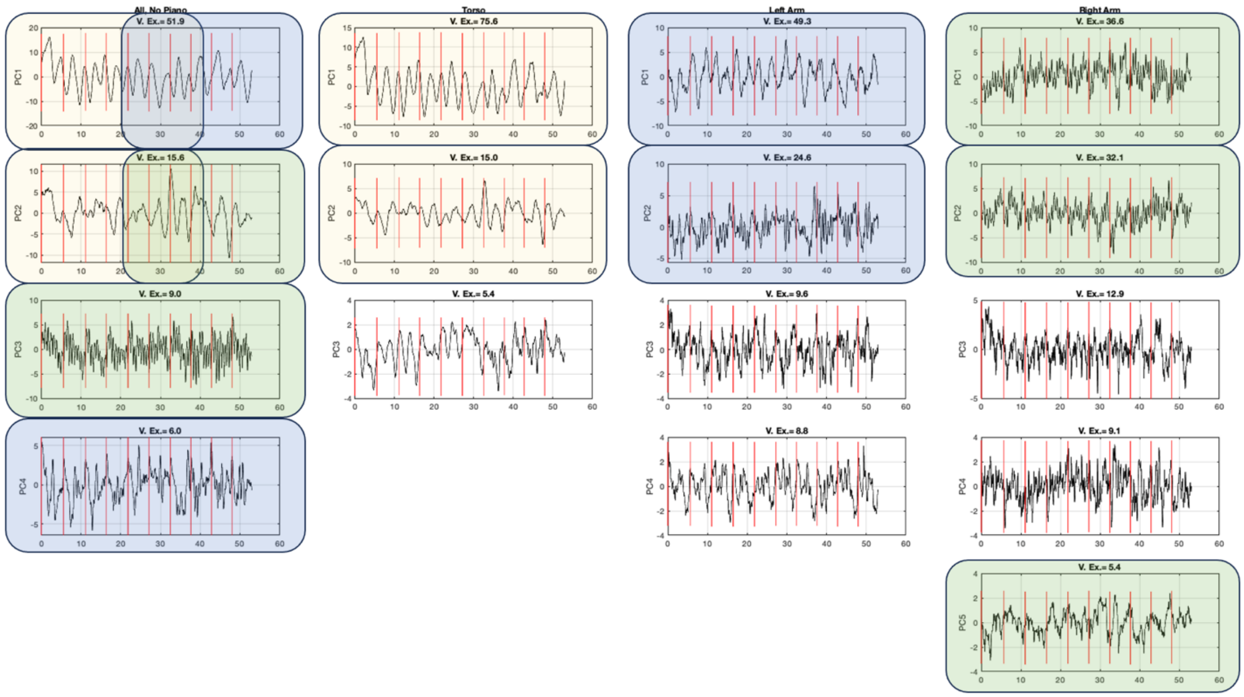
For exercise 12b, the left-arm subspaces occur with higher ranking PCs in PCA^{all}, as had occurred for the right-arm subspaces for exercise 12a. Subspaces unique to the left hand occur in the pair $PC4^{all} \approx PC2^{left}$ [41 degrees] and $PC7^{all} \approx PC4^{left}$ [42], as highlighted by the red rectangles in figure 7.18. The PCs in these pairs do not relate to any other PCs in either PCA^{torso} or PCA^{right}, so they can be considered one-dimensional PC subspaces describing unique coordination features of the left hand during this performance. As in exercise 12a, the hand performing the chromatic scale passage appears to have unique subspaces with PCA^{all}, but they account for less of the overall variance compared to subspaces associated with the torso and the arm performing the staccato quarter notes. The left-hand subspaces found in exercise 12b may arise due to participant-specific coordination choices for executing the task parameters.

However, due to the pervasiveness of task-determined patterns related to note-striking frequencies in the right and left-hand parts of the musical score, it is difficult to sort variation characteristics related to participant choices from those arising from task requirements.

As occurred for exercise 12a, the inter-PC angles comparing PCs from the right and left arms were mostly very high, except for $PC5^{right} \approx PC5^{left}$ [41 degrees], as highlighted by the black rectangle in figure 7.19. PC5 accounts for a small amount of the variance in both PCA^{left} and PCA^{right}: $PC5^{left}$ (2.7%) and $PC5^{right}$ (2.6%). This suggests that the variation of the right and left arm is mostly independent, but that a small amount of the variation is coordinated between the two for 12b, which was not evident in 12a. A second notable difference in the distribution of variance between the right and left arms for exercises 12a and 12b is that PCs corresponding to the hand performing the legato chromatic passages form clearer subspaces in relation to PCA^{all} when the left hand plays them (exercise 12b, figure 7.18) than when the right hand plays them (exercise 12a, figure 7.15). In other words, the chromatic passage contributes a greater amount of overall variance to the dataset when the left hand performs it than when the right hand performs it. It is unlikely that this difference is dictated by task parameters since the task parameters are symmetrical between the two exercises, but rather reflects unique coordination characteristics of the participant. In the case of participant 4, the greater variation associated with the left-hand chromatic passage may have arisen due to handedness. This participant is left-handed and may have intuitively chosen to utilize more degrees of freedom in the left-hand chromatic passages due to better dexterity and more precise control of note timing and loudness. A possible explanation is that the participant may have intuitively chosen to limit the movement in their non-dominant right hand (freezing degrees of freedom) to minimize movement not essential to note-execution.

Figure 7.17

PC Waveforms from Participant 4's Performances of Exercise 12b, Trial 1



Note. The chromatic passage is in the right hand for exercise 12a. Yellow = 'all' compared to 'torso'. Blue = 'all' compared to 'left arm', and green = 'all' compared to 'right arm'. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

Table 7.5

Summary of PC Similarity Pairs from Participant 4's Performance of Exercise 12b, Trial 1

	PC Similarity Pairs and Inter-PC Angles (°)		
PCA Subgroup	Torso	Left Arm	Right Arm
All	PC1 ≅ PC1 15	PC1 ≅ PC1 28	PC3 ≅ PC1 46
	PC2 ≅ PC2 21	PC4 ≅ PC2 41	PC3 ≅ PC2 50
		PC2 ≅ PC5 42	PC8 ≅ PC4 50
		PC7 ≅ PC4 42	PC2 ≅ PC5 51

Figure 7.18

PC Subspace Identification Map for PCA^{all} and PCA^{left} (PCs ≥ 2%), Participant 4, Exercise 12b, Trial 1

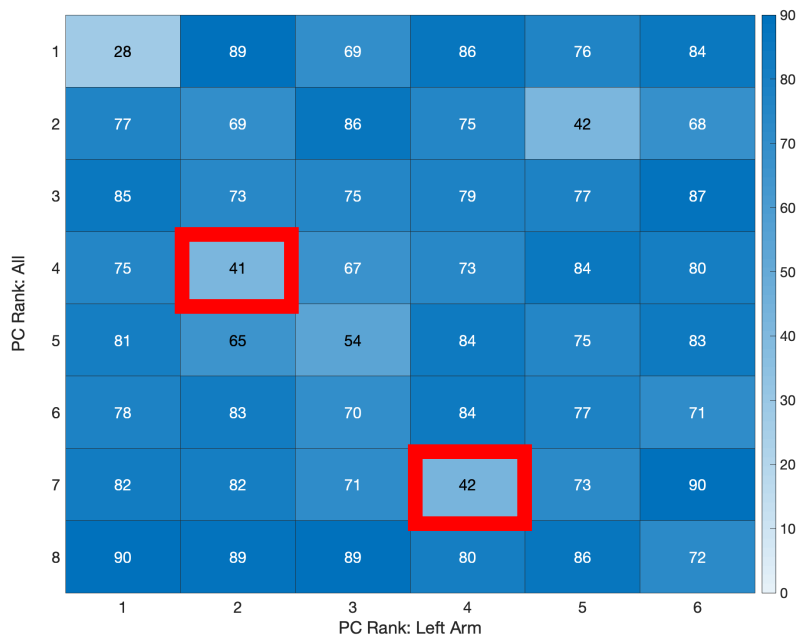
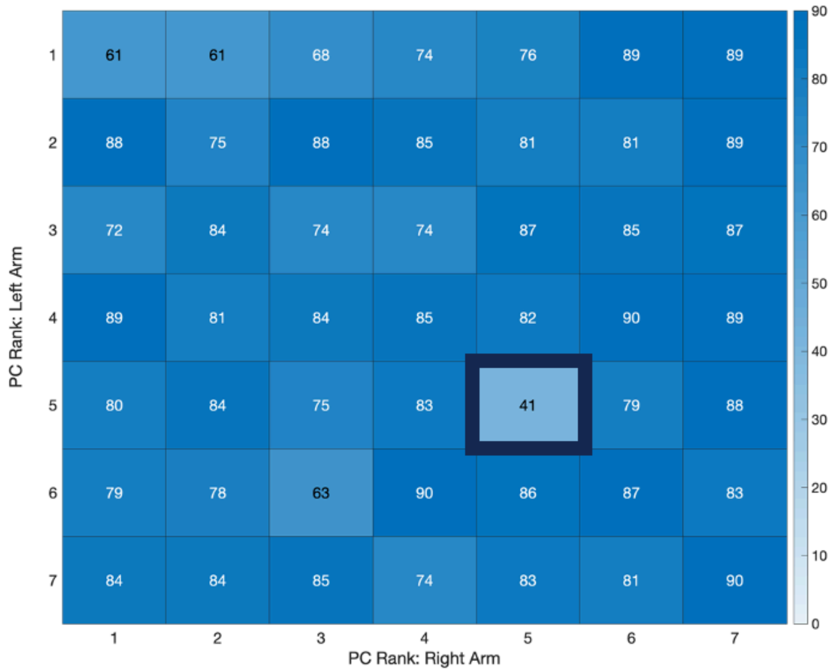


Figure 7.19

PC Subspace Identification Map for PCA^{left} and PCA^{right} (PCs $\geq$ 0.5%), Participant 4, Exercise 12b, Trial 1



7.4.1.4 Summary of Results Part I: Influence of Task Constraints on One-Dimensional PC Subspaces. The examples presented in the previous section serve to illustrate the value of functional subspace identification for gaining insight into task-dependent variation in a complex motion capture data set. They provide evidence that the tool of PC subspace identification identifies invariant subspaces where we expect to find them based on task constraints. Conducting PCA on independent subgroups of the data and comparing them with a global PCA conducted on all the data simultaneously highlights coordinative features related to task-parameters, such as the dominance of the alternating variation pattern persisting throughout PCs in tasks that require cyclical x-axis displacement of the hands (parallel scales), or the independence of PC patterns between the torso and the arms in tasks where the arms are free to move independently of the torso (two-note slurs). Functional subspace identification was also able to distinguish unique subspace characteristics for the right and left arm when they were executing different musical patterns in each hand (chromatic five-finger passage). By examining these subspaces across many examples outside of those presented in this paper, we have confirmed that these types of task-determined subspace characteristics are consistent across performances of the task by different participants in this study, suggesting they arise from parameters defined in the musical score. The subspace characteristics highlighted in Part I of the results section do not relate to participant-specific coordination characteristics that may arise from performers' musical or biomechanical choices. In fact, their dominance in the larger PCs may be masking participant-specific variation features that could help researchers understand individual performers' unique coordination characteristics. Although task-determined patterns are not in themselves useful for identifying pianist's unique coordination characteristics and tracking how they respond to movement retraining interventions, our analysis suggests that functional subspace identification is useful for defining task-related variance more easily in complex data sets. It is important for researchers to be capable of defining task-determined variation patterns to devise strategies for separating them from the data, allowing future research to target participant-specific variation related biomechanical and musical choices.

Some of the examples in Part I of the results section, such as the contrasting subspace characteristics of exercises 12a and 12b for participant four, hinted at the existence of participant-specific subspaces that may be detectable in pairs of smaller PCs accounting for less of the overall variance. The following section probes more deeply into instances of one-dimensional subspaces that point to participant-specific features in the variation of the motion capture data that may be related to an individual's movement choices.

7.4.2 Results Part II: Participant-Specific One-Dimensional PC Subspaces

Variation in musical performance can arise from pre-determined sources related to variation patterns in the task, and from anatomical constraints imposed by the structure and function of the human body (Beacon, Russell, Comeau, 2023b). Therefore, the independence of PCs from different functional groups and the existence of one-dimensional PC subspaces can be influenced by variation inherent in the task (as in the examples in results, part I), or variation introduced by the performers' musical and biomechanical choices. The following section explores examples of one-dimensional PC subspaces that are not expected based on task parameters and are therefore likely to represent unique coordination characteristics of individual performers.

The one-dimensional PC subspaces discussed in the subsequent section fall into two categories. The first kind of subspace occurs when similar PC waveforms are identified in both the global PCA conducted on all the data and in one or more of the independent PCAs conducted on subgroups of the data. In this case, the data in the subgroup is also present in the global PCA. The presence of a one-dimensional subspaces between PCA^{all} and a $PCA^{subgroup}$ identifies variation patterns existing independently within the larger data set that can be linked to the movements of the variables included in the subgroup. A second form of subspace are those that exist between similar PC pairs from completely independent subgroups of the data, such as the right and left arm, or between one of the arms and the torso. In this case, none of the data of one subgroup is included in the other. The presence of a one-dimensional PC subspace between independent data groups presents evidence that the two subgroups are coordinated. For instance, if a PC subspace occurs between PCA^{left} and PCA^{right} it suggests that some aspect of the movement of the right and left arm is coordinated. A subspace occurring between one of the two arm groups and the torso groups can give an indication of whether the arm is moving or independently of the torso. Subspace relationships between subgroups could arise due to task-dependent variation, or variation related to performer's choices. Comparing subspace characteristics between participants for a given task, or between the right and left arm in symmetrical or parallel playing tasks can give an idea about whether a given subspace relates more strongly to task-parameters or participant-specific variation patterns.

The following sections present examples of how functional subspace identification can be used to identify participant-specific coordination characteristics in two scenarios. Part II (a) identifies participant-specific coordination characteristics in symmetrical contrary motion scale playing. Part II(b) identifies participant-specific coordination characteristics in a parallel whole-tone octave scale.

7.4.2.1 Results Part II (a)-Using PC Subgroups to Identify Participant-Specific Coordination Characteristics in Scale Playing. Performing scales is a fundamental part of pianists' musical education and most pianists continue practicing scales regularly throughout their lives to maintain finger dexterity and to warm up before performing. The C-major parallel and contrary motion scales performed in this study are among the earliest exercises students learn to play on the piano and the skilled pianists participating in this study have practiced these exercises since early childhood. It is likely that each pianist will have developed a habitual manner of playing these scales over many years of repetition. Scales also provide a good opportunity to examine differences in right and left arm movement patterns since both hands must execute the same pattern of notes and rhythm simultaneously. As such, studying scale performances is a practical starting point for assessing the ability of functional subspace identification to help identify participant-specific coordination characteristics in piano playing.

We chose to investigate contrary motion scales first, since the symmetrical arrangement of notes and fingering permit direct comparison of right and left arm movements during time-synchronized performance of identical musical and biomechanical task parameters. We began by examining the corresponding PC subspace identification maps from independent PCs conducted PCA^{all}, PCA^{torso}, PCA^{left} and PCA^{right} for each of the six pianists' performances of contrary motion scales across all the three trials to search for low inter-PC angles between PC pairs that could point to one-dimensional PC subspaces between different functional groups of the data. Next, we cross-referenced identified invariant PC subspaces with plots of the PC waveforms (≥ 2% variance).

A survey of the contrary motion scale data across the six pianists revealed that the scale performances of most participants in this study could be broadly categorized either as consistently symmetrical or consistently asymmetrical. The PC subspace characteristics of consistently symmetrical scale performers tended to show low inter-PC angles between PC pairs in the right and left arms, including between smaller PCs ranked higher than two. When a similar set of PCs can be used to describe the variance of both the right and left arm, it follows that the right and left arms move more symmetrically during the performances because the independent right and left arm data sets can be represented by a similar group of PC vectors. Additionally, symmetrical performers' right and left arm PCs tended to form subspace pairs with many of the same PCs of PCA^{all} and PCA^{torso}. This suggests that both the right and left arm data sets tended to explain the same variation patterns in the larger data set, and that any arm variation related to the torso was similar for both the right and left arms.

By contrast, the right and left arm PCs of consistently asymmetrical performers tended show low inter-PC angles for only the first, or first and second PCs. Subspace pairs between PCs ranked three or higher tended to be absent or weakly related in the asymmetrical performers. When a different set of PCs is required to describe the variance of the right and left arms, the movements of the right and left arms must have distinct qualities due to asymmetries in arm movement. Additionally, the right and left arm PCs of asymmetrical performers tended to have one or more unique subspaces with PCs in the torso or all groups that was not shared by the other arm. This suggests that part of the variance in the right and left arms contribute distinct variation patterns to the larger data set in asymmetrical performances. It also suggests that the right and left arms may have different coordination characteristics than each other with respect to the torso in asymmetrical performers.

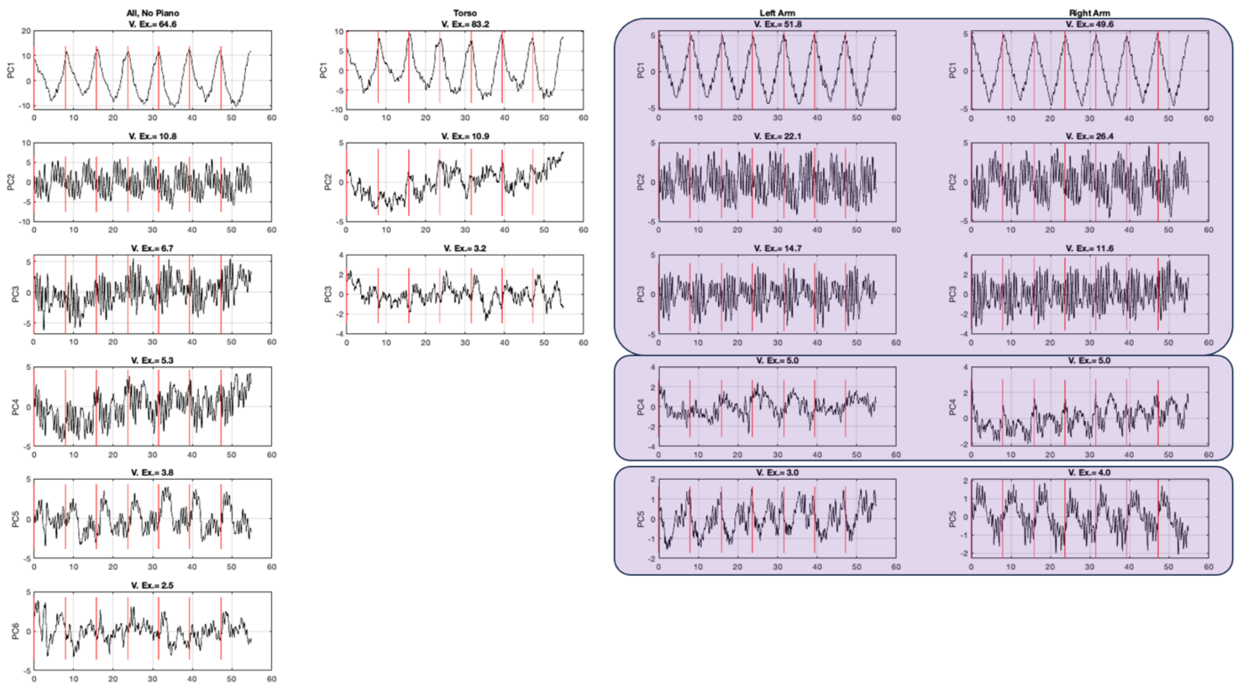
Based on these characteristics, we found that participants 2 and 4 could be considered consistently symmetrical scale performers, while participants 1, 3, and 5 could be considered consistently asymmetrical performers. Participant 6 exhibited some symmetrical and some asymmetrical qualities. The following examples illustrate how we arrived at these categorizations using PC subspace identification.

7.4.2.1.1 Symmetrical Contrary Scale Performances. Figure 7.20 displays the PC waveforms of participant 2 and 4 for trial one. The subsequent figure 7.21 displays participant 2 and 4’s PC subspace identification maps comparing right and left arm PCs for trial 1. The purple-coloured blocks in figure 7.20 highlight arm PCs that are related based on the angles in the PC subspace identification maps. PCs forming subspace pairs with a PC in another row are marked with arrows. As expected based on the symmetry of the task, the PC subspace identification maps displayed low inter-PC angles between $PC1^{right} \approx PC1^{left}$ and $PC2^{right} \approx PC2^{left}$ pairs for both participants (figure 7.21). However, participants 2 and 4 also had subspace pairs between some right and left arm PCs ranked three or higher. For participant 2, subspaces occur between $PC3^{right} \approx PC3^{left}$ [28 degrees], and $PC5^{right} \approx PC5^{left}$ [37 degrees] (figure 7.21, A). Although it does not form a pairwise subspace, $PC5^{right}$ appears to share variation characteristics with both $PC4^{left}$ and $PC5^{left}$ with inter-PC angles of 60 and 64 degrees, respectively (figure 7.21, A). Participant 4 has two subspaces between arm PCs ranked three or higher: $PC3^{right} \approx PC4^{left}$ [40 degrees] and $PC4^{right} \approx PC5^{left}$ [48 degrees] (figure 7.21, B). The similarity of right and left arm PCs for these two participants suggests they are exhibiting symmetrical arm coordination characteristics.

Figure 7.20

PC Waveforms ≥ 2% Variance for Participant 2 and 4's Contrary Scales, Trial 1

A) Participant 2



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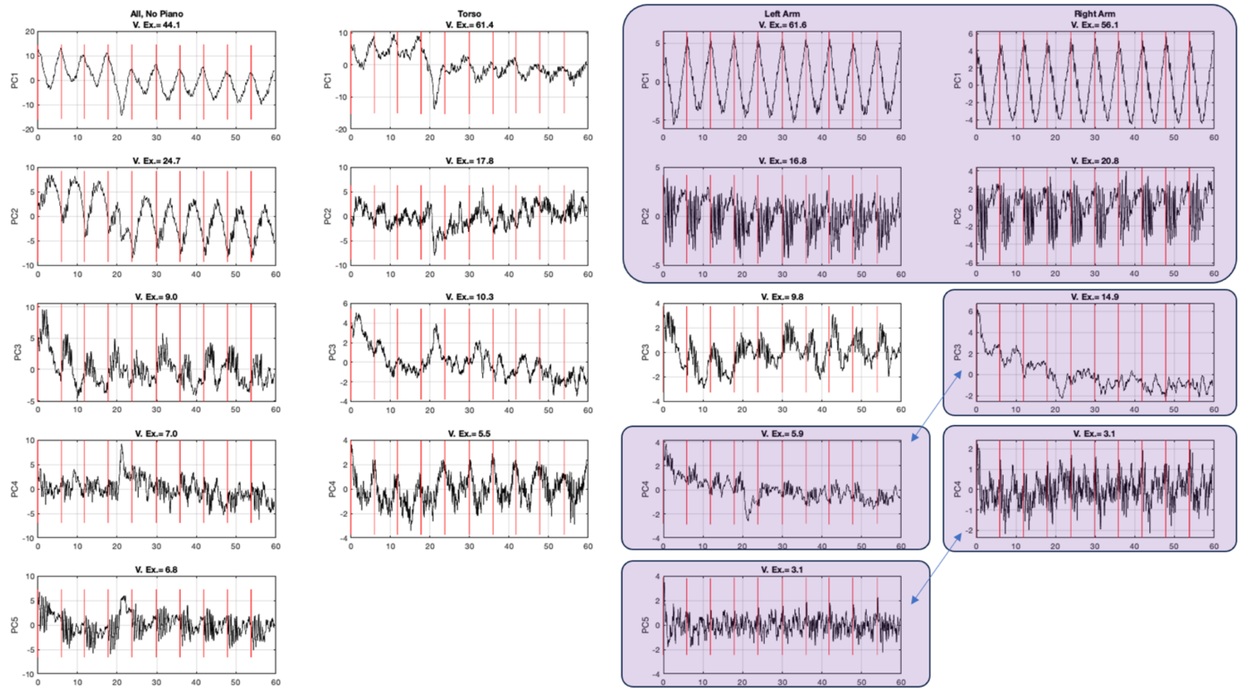
B) Participant 4

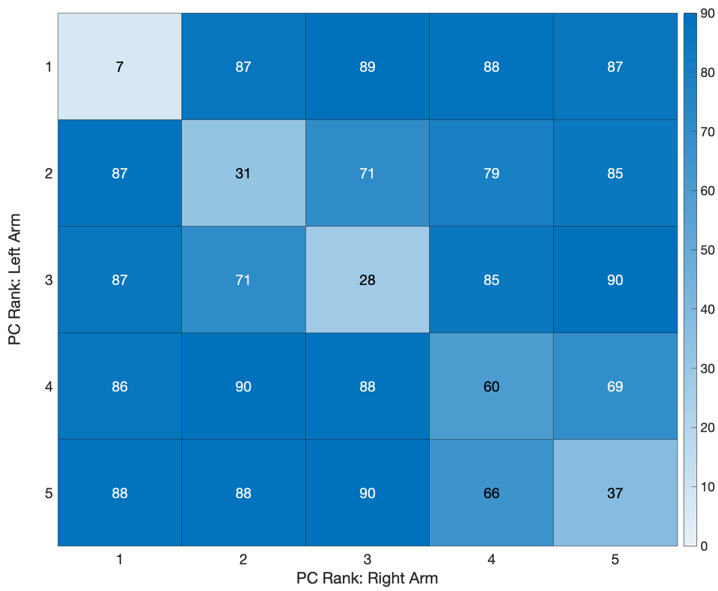


Note. The purple-coloured blocks highlight PC subspaces between PCA^{left} and PCA^{right}. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

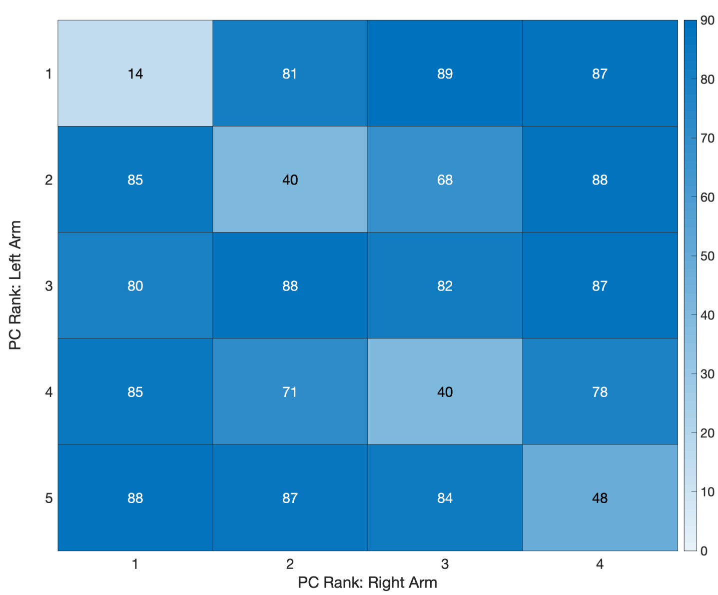
Figure 7.21

PC Subspace Identification Maps Comparing Right and Left Arm PCs for Participant 2 and 4, Contrary Scales, Trial 1

A) Participant 2



B) Participant 4



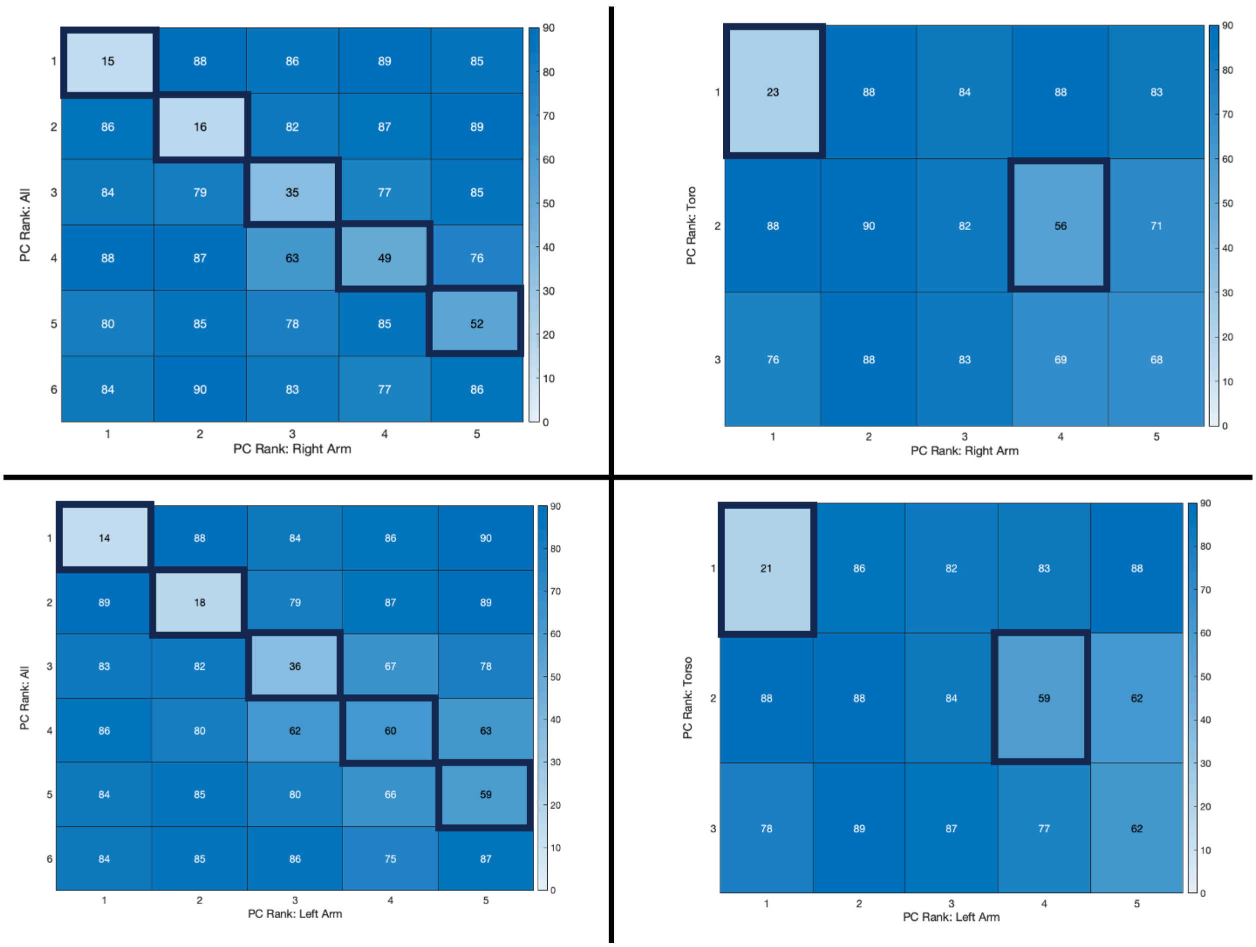
Furthermore, related PCs in PCA^{left} and PCA^{right} created subspace pairs with many of the same PCs in PCA^{torso} and PCA^{all} for participants 2 and 4. For example, the inter-PC angles highlighted by black rectangles in the upper and lower left quadrants of figure 7.22(A) show that both the right arm and left arm share low inter-PC angles with the same PCs in PCA^{all} for participant 2, suggesting that the right and left arm data represent similar variation patterns contained within the larger data set. The upper and lower right quadrants of figure 7.22 (A) shows that subspaces exist between not only between $PC1^{torso}$ and PC1 of each arm, but also between $PC2^{torso}$ and PC4 of each arm. This suggests that the right and left arm of participant 2 coordinate in a similar manner with respect to the torso.

For participant 4, figure 7.22(B) shows that related PCs from PCA^{left} and PCA^{right} also create subspaces with the same PCs in PCA^{torso} and PCA^{all}. However, as can be seen in the PC waveforms earlier in figure 7.20(B), participant 4's left arm has one more PC than their right arm. The absence of any low inter-PC angles in row three of the subspace identification map in figure 7.21(B) suggests that $PC3^{left}$ represents unique left arm variation which does not form subspaces with any right arm PCs. Due to the presence of the unique $PC3^{left}$ the PC numbers do not align between all PC pairs of the arms. The waveform represented by $PC4^{left}$ corresponds to $PC3^{right}$ and the waveform represented by $PC5^{left}$ corresponds to $PC4^{right}$ (figure 7.20,B). Therefore, the subspaces formed with PCA^{torso} and PCA^{all} appear to be similar for the right and left arm, as highlighted by the black rectangles in figure 7.22(B). Interestingly, we were unable to find a strong subspace pair for the unique $PC3^{left}$ in relation to either PCA^{all} or PCA^{torso}. We hypothesized that this unique left arm PC may form a subspace pair with a smaller PC in PCA^{right} or PCA^{all}. To test this hypothesis, we lowered the variance threshold to 0.5%. This revealed another subspace pair between $PC3^{left} \approx PC5^{right}$ [47 degrees]. This suggests that the variation related to this pattern occurred in both the right and left arm but accounted for a smaller percentage of the overall variance in the right arm (1.9%) compared to the left arm (9.8%).

Figure 7.22

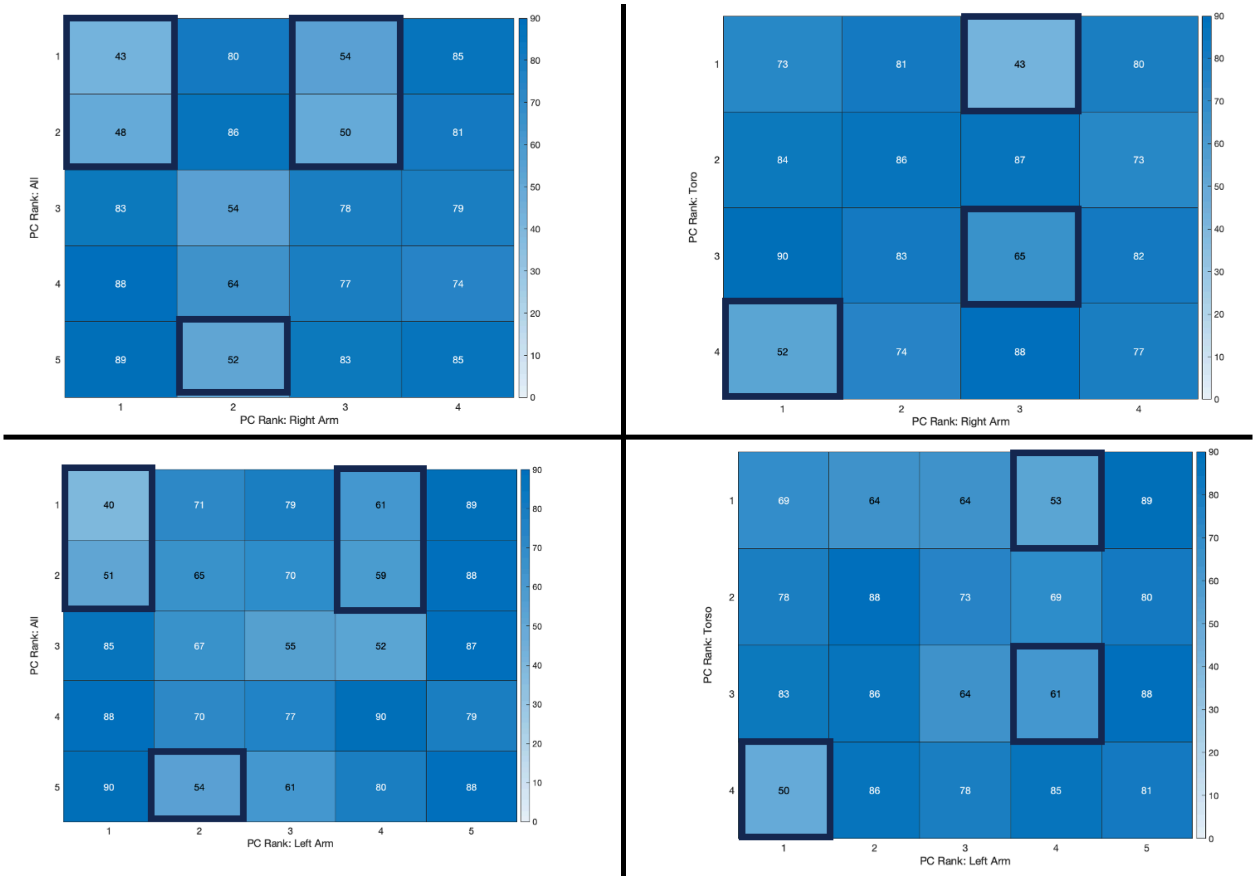
PC Subspace Identification Maps Comparing Each Arm with Torso and All PCs for Participant 2 and 4, Contrary Scales, Trial 1

A) Participant 2



(figure continued on next page)

B) Participant 4



We noted similar symmetrical subspace characteristics in trials two and three for participants 2 and 4 for the contrary scale task. This suggests that those participants' symmetrical coordination characteristics were largely stable across the three-week trial. We will undertake a comprehensive study of the stability of subspace characteristics across repeated performances in future research.

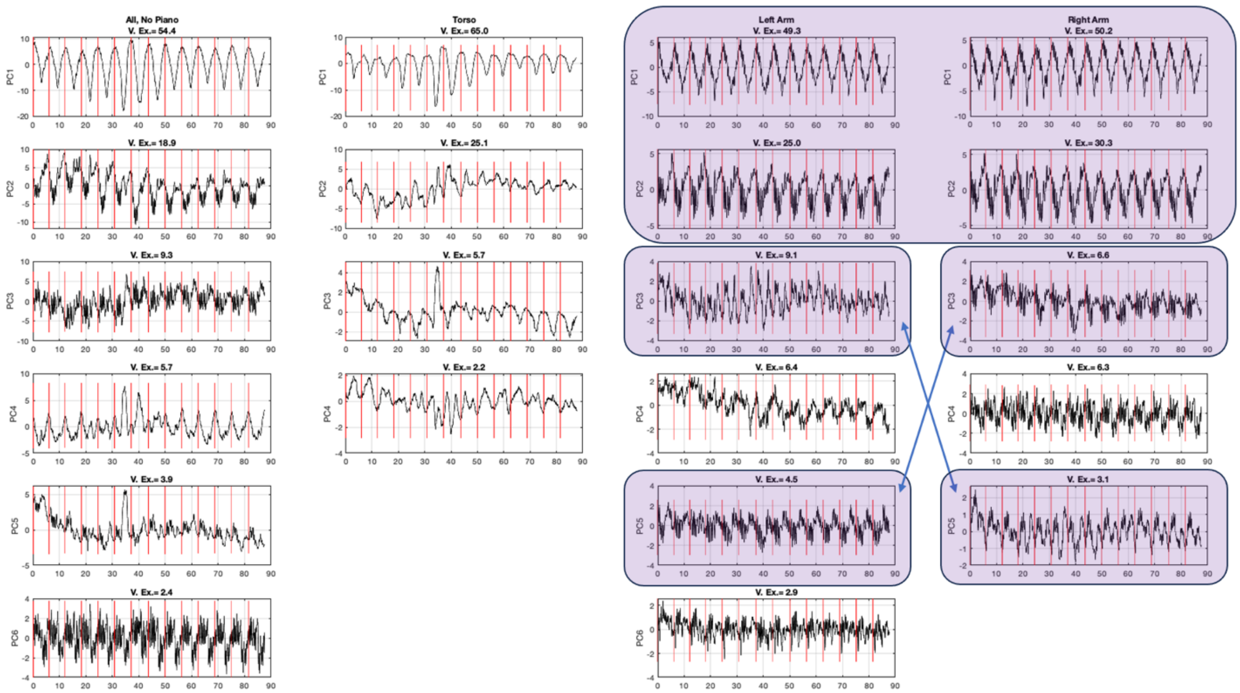
7.4.2.1.2 Asymmetrical Contrary Scale Performances. In contrast to the symmetrical subspace characteristics exhibited by participants 2 and 4, participants 1, 3, and 5 displayed evidence of asymmetrical coordination characteristics between the right and left arms, despite the task's symmetrical construction. Figure 7.23 displays the PC waveforms for participants 1, 3, and 5's contrary scales performances in trial one, while figure 7.24 displays the corresponding right and left arm PC subspace identification maps. The purple-coloured blocks in figure 7.23 highlight similar waveforms that form subspace pairs. As was the case for participants 2 and 4, the $PC1^{left} \approx PC1^{right}$ and $PC2^{left} \approx PC2^{right}$ pairs shared low inter-PC angles ranging from 8 degrees to 30 degrees, except in the case of the pair $PC2^{left} \approx PC2^{right}$ [55 degrees] of participant 3, which had a somewhat higher inter-PC angle. Since the $PC1^{left} \approx PC1^{right}$ and $PC2^{left} \approx PC2^{right}$ tended to share low inter-PC angles across all six participants, it is reasonable to consider that most of the variance they explain relates to task-determined variation, and not to participant-specific coordination choices.

However, similarities between higher ranking right and left PCs were not as clear for participants 1, 3, and 5 as they were for participants 2 and 4, suggesting that the higher numbered arm PCs tended to describe distinct variation characteristics in each arm. For participant 1, mid to high inter-PC angles ranging from 43 to 63 degrees are distributed among multiple component pairs between PCs 3 to 6 in the left arm and PCs 3 to 5 in the right arm (figure 7.24, A). The absence of low inter-PC angles exclusive to pairs of PCs ranked three or higher in the right or left arm prevents us from identifying participant-specific subspaces common to both arms for participant 1's contrary scales and suggests the arms moved with a high degree of independence. For participant 3 (figure 7.24, B), PC subspaces other than $PC1^{left} \approx PC1^{right}$ [8 degrees] were detectable for two pairs: $PC4^{left} \approx PC5^{right}$ [39 degrees] and $PC3^{left} \approx PC3^{right}$ [46 degrees]. However, $PC4^{right}$ and $PC6^{right}$ appeared to be completely independent of any PCs in the left arm, sharing no inter-PC angles lower than 78 degrees with any left arm PCs. It is likely that that $PC4^{right}$ and $PC6^{right}$ represent variation patterns that are unique to participant 3's right arm. Interestingly, $PC2^{left}$ did not share a strong relationship with $PC2^{right}$ or any other PC in the right arm, further suggesting that many aspects of participant 3's right and left arm movement vary independently in this task. For participant 5 (figure 7.24, C), right and left arm subspaces occurred in the pairs $PC1^{left} \approx PC1^{right}$ [19 degrees] and $PC2^{left} \approx PC2^{right}$ [30 degrees]. Higher inter-PC angles ranging from 52 to 71 degrees were distributed among multiple PC pairs between PCs 3 to 5 in the right and left arm. No PC subspaces were apparent in PC pairs ranked three or higher suggesting that outside of the task-determined variation, the right and left arms varied independently in this task for participant 5. Taken together, the infrequency of higher-ranking PC subspaces between the right and left arm suggest that the right and left arm movements are less symmetrically coordinated for participants 1, 3 and 5 compared to participants 2 and 4.

Figure 7.23

PC Waveforms ≥ 2% Variance for Participant 1, 3 and 5's Contrary Scales, Trial 1

A) Participant 1



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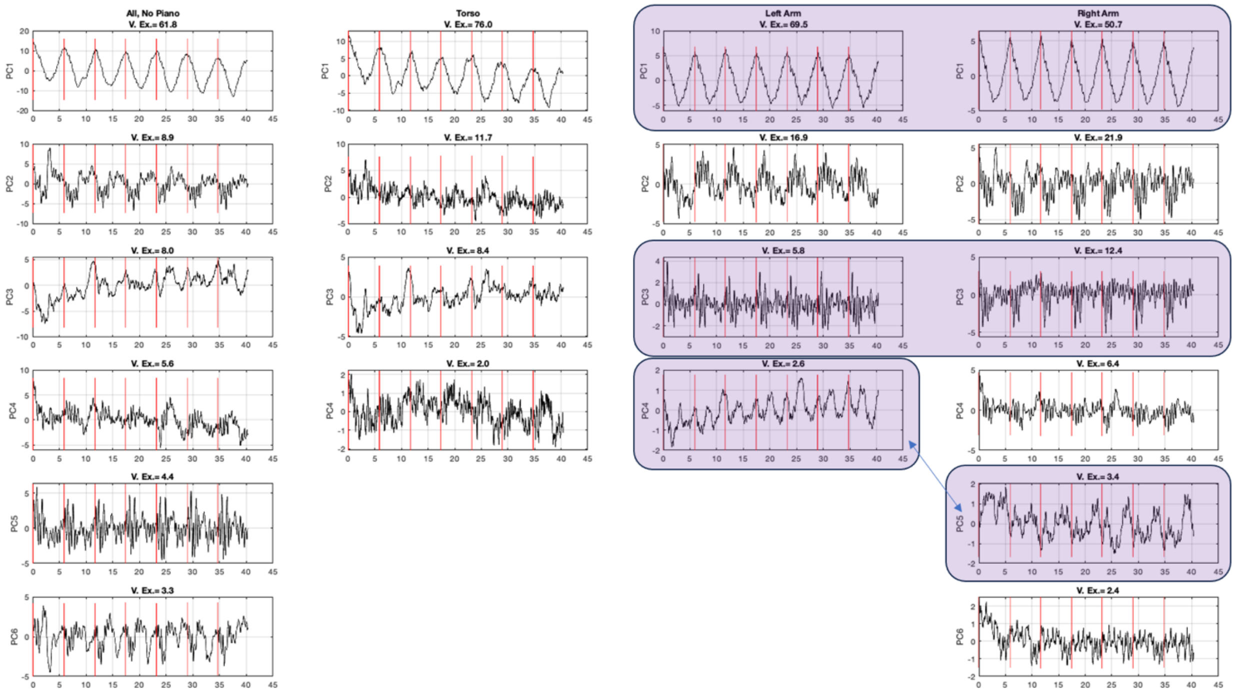
B) Participant 3



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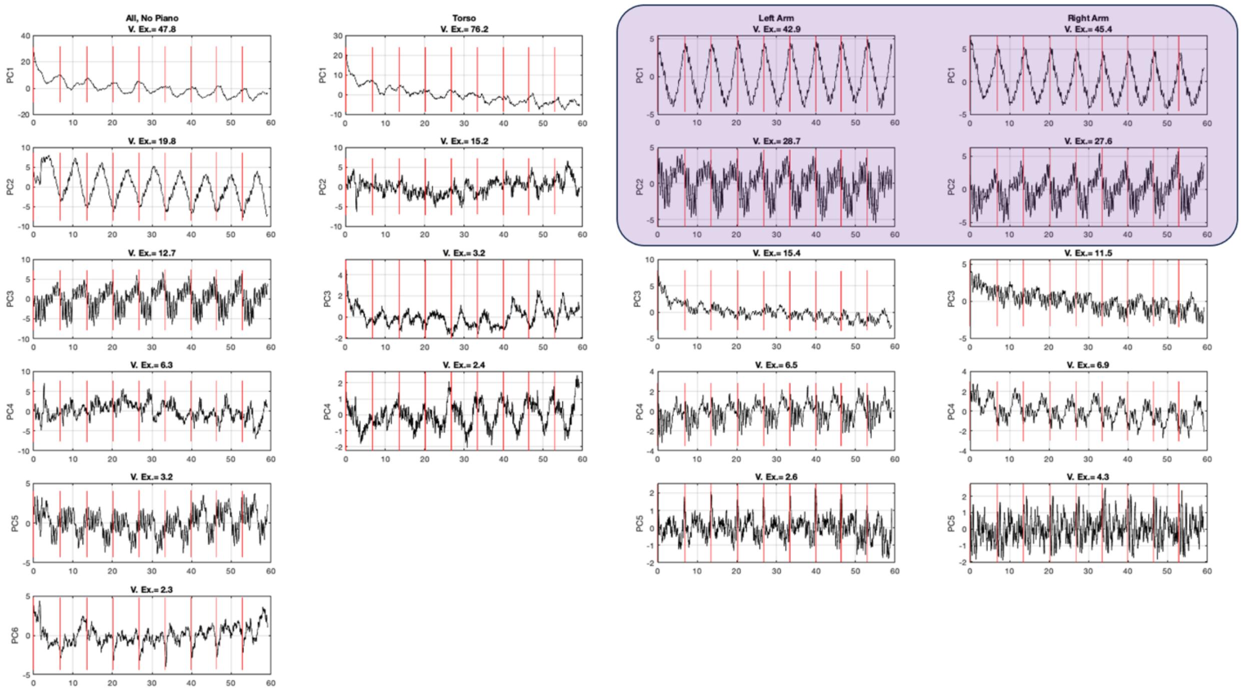
C) Participant 5

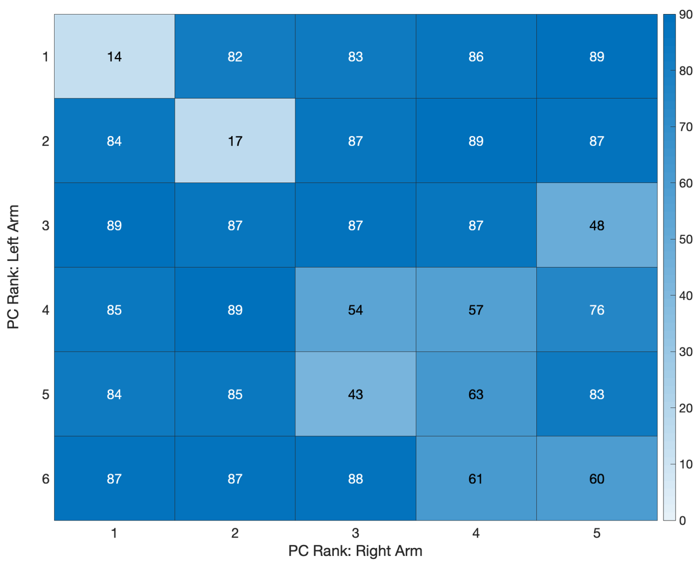


Note. The purple-coloured blocks highlight PC subspaces between PCA^{left} and PCA^{right}. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

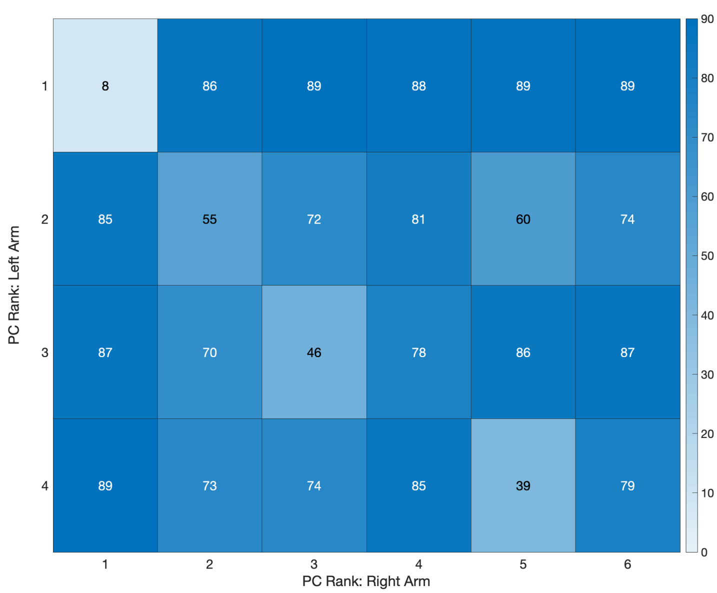
Figure 7.24

PC Subspace Identification Maps Comparing Right and Left Arm PCs for Participant 1, 3, and 5 Contrary Scales, Trial 1

A) Participant 1



B) Participant 3



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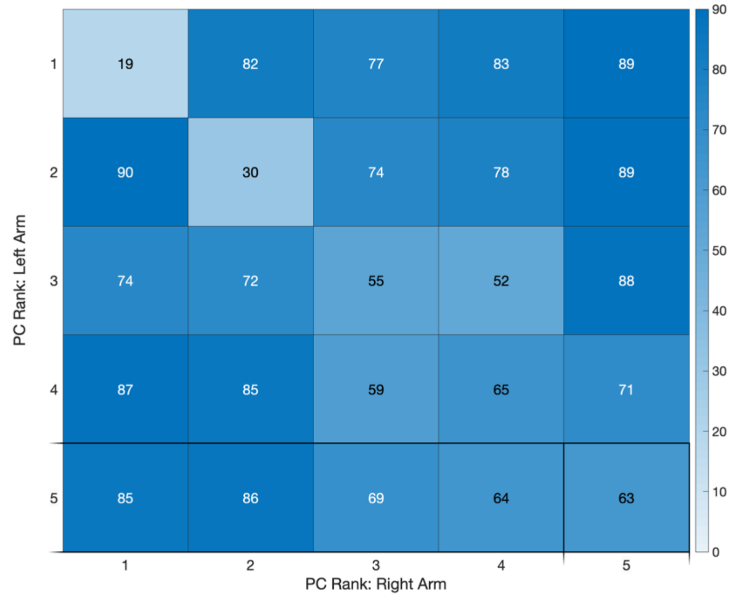
C) Participant 5



The more asymmetrical performers also displayed different subspace characteristics for the right and left arms when comparing them to PCA^{all} and PCA^{torso}. Figures 7.25 (A), (B), and (C) highlight relationships between the arms and both PCA^{all} and PCA^{torso} for participants 1, 3, and 5. Inter-PC angles highlighted in black squares indicate relationships with PCA^{all} and PCA^{torso} common to both arms. Green squares signify relationships with PCA^{all} or PCA^{torso} that are unique to the right arm. Red squares signify relationships with PCA^{all} or PCA^{torso} that are unique to the left arm. A yellow arrow connecting boxes indicates that a single component in PCA^{all} and PCA^{torso} (a row) has a series of weaker inter-PC angles with multiple arm PCs (columns), preventing identification of a unique subspace within a single PC pair.

For participant 1, the expected subspaces exist between pairs $PC1^{all} \approx PC1^{left}/PC1^{right}$ and $PC2^{all} \approx PC2^{left}/PC2^{right}$, reflecting variation related to task parameters. However, a unique right arm subspace exists between $PC6^{all} \approx PC4^{right}$ [22 degrees], highlighted by the green square in the bottom row of the subspace identification map in the upper left quadrant of figure 7.25(A). $PC4^{right}$ does not relate to any left arm PCs and therefore represents a unique one-dimensional PC subspace that exists independently within the complete data set. Variation summarized by this PC is linked to movement in the anatomical markers included in the right arm group, providing evidence that the right arm moved differently than the left. There is evidence of a second right arm subspace in the pair $PC4^{all} \approx PC5^{right}$ [47 degrees], highlighted by the green square in the fourth row of the subspace identification map in the upper left quadrant of figure 7.25(A). Although this inter-PC angle is higher than the one defining the previous subspace, it stands out as the lowest inter-PC angle of any PC pair including either $PC4^{all}$ or $PC5^{right}$. A unique left arm subspace is apparent in the pair $PC6^{all} \approx PC5^{left}$ [44 degrees], highlighted by the red square in lower-left quadrant of figure 7.25(A). Even though both $PC5^{left}$ and $PC5^{right}$ share subspaces with PCA^{all}, they are distinct subspaces because the $PC5^{right}$ and $PC5^{left}$ are not related ($PC5^{left} \neq PC5^{right}$ [83 degrees]), and because they relate to different PCs within PCA^{all}. Therefore, $PC5^{right}$ and $PC5^{left}$ represent unique variation patterns that can be identified independently within the complete data set. There are no clear examples of low inter-PC angles between the torso and the arms, suggesting that PC subspaces cannot be identified between the torso and the right and left arms outside of the task-dependent pairs $PC1^{torso} \approx PC1^{left}$/ $PC1^{right}$. However, weaker inter-PC angles ranging from 52 to 66 degrees occur between different torso-arm PC pairs for the right and left side arms, as highlighted by the green and red squares in the upper and lower right quadrants of figure 7.25(A). This suggests that participant 1's arms movements are mostly independent of the torso, and that any weak relationships that may exist between the arms and torso relate to different PCs in the right and left arm.

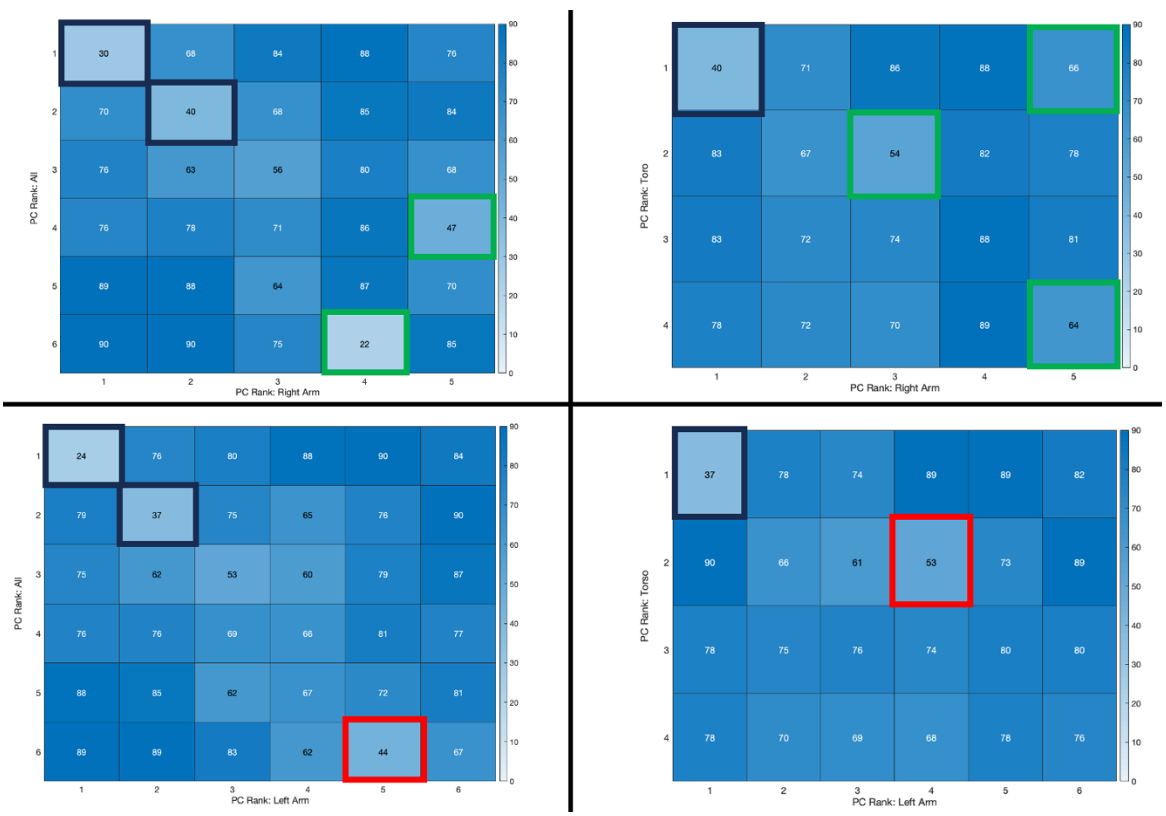
In the case of participant 3, the black squares in figure 7.25 (B) highlight that many of the PC subspaces formed between pairs in PCA^{right} and PCA^{all} are similar to those formed by PC pairs between PCA^{left} and PCA^{all}. This suggests that many of the right and left arm PCs represent similar variation within the larger data set. However, the green square in the upper-left quadrant of figure 7.25(B) highlights a PC subspace unique to the right arm: $PC4^{all} \approx PC4^{right}$ [51 degrees]. $PC4^{right}$ does not relate to any left arm PCs, so it likely represents a subspace unique to the right arm that varies independently within the larger data set. The right and left arms do not appear to share any variation characteristics with the torso outside of the $PC1^{torso} \approx PC1^{left}/PC1^{right}$, as highlighted by the black squares in the upper and lower right quadrants of figure 7.25(B). However, a unique subspace exists in the pair $PC3^{torso} \approx PC4^{left}$ [42 degrees], highlighted by the red box in the lower right quadrant of figure 7.25(B). This suggests that the left arm may have unique coordination characteristics with the torso that do not exist between the right arm and the torso. Taken together, these subspace characteristics suggest that although much of the right arm and left arm variation can be represented by similar PCs, the right arm shares unique variation characteristics with PCA^{all} that are not evident for the left arm. Additionally, although much of the variation in the torso and the arms is independent, the left arm shows evidence of coordination with the torso that the right arm does not.

In the case of participant 5, the black squares in figure 7.25(C) highlight that PCs within PCA^{right} and PCA^{left} create many of the same subspace pairs with respect to PCA^{all} and PCA^{torso}. As was the case for participant 3, these similar PC subspaces suggest much of the variance of right and left arm can be described by a similar set of PCs. However, the red squares in the lower left and lower right quadrants of figure 7.25(C) highlight a unique subspace between the pairs PC1^{all} ≈ PC3^{left} [35 degrees] and PC1^{torso} ≈ PC3^{left} [27 degrees]. This suggests that PC3^{left} has a strong relationship to PC1^{torso} that is not evident in the right arm. Instead, PC1^{all} and PC1^{torso} have weak relationships with multiple right arm PCs, as is indicated by the yellow arrows in the upper right and left quadrants of figure 7.25(C). Taken together, these subspace characteristics suggest that participant 5's right arm moves more independently of the torso, while the left arm is more coordinated with the torso. These subspace characteristics are similar to those displayed by participant 3.

Figure 7.25

PC Subspace Identification Maps Comparing Each Arm with Torso and All PCs for Participants 1, 3 and 5, Contrary Scales, Trial 1

A) Participant 1



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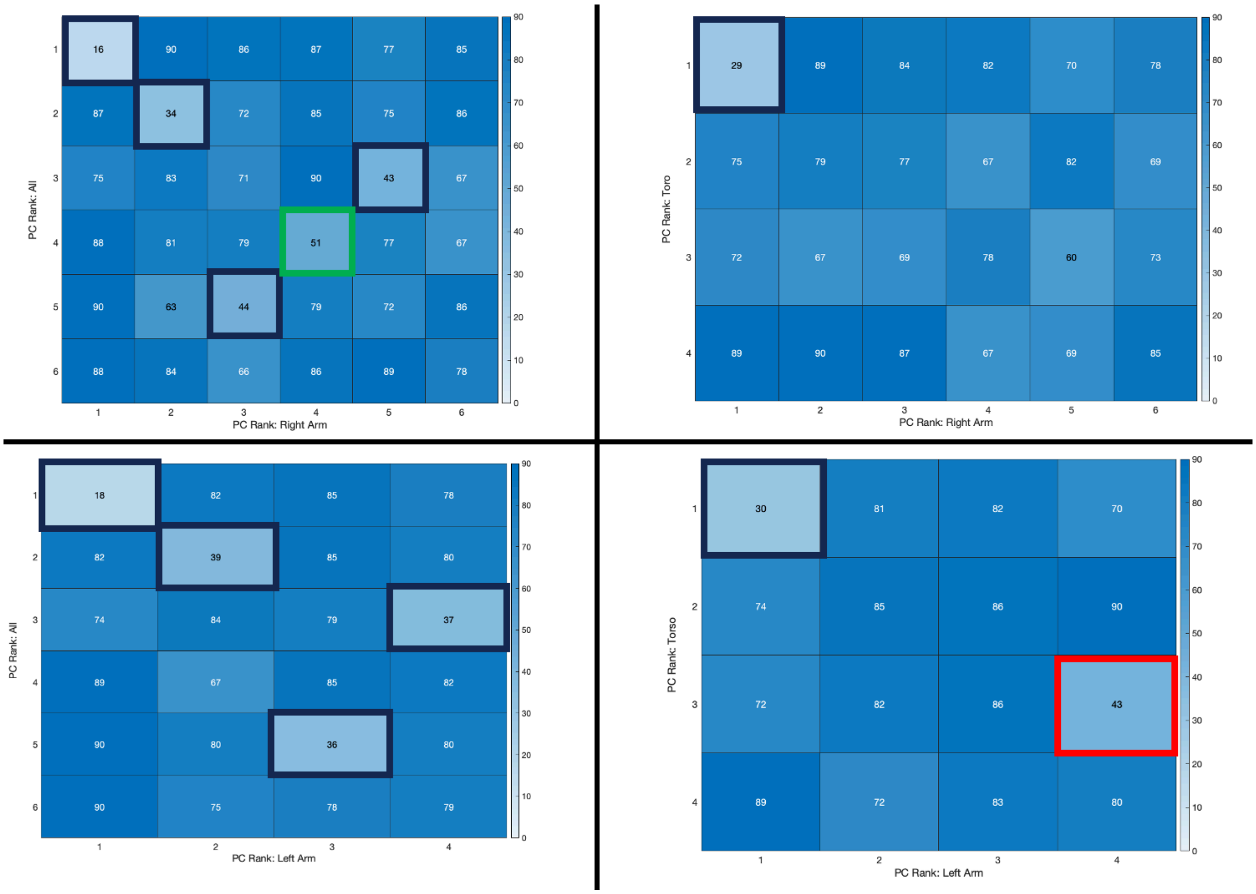
B) Participant 3



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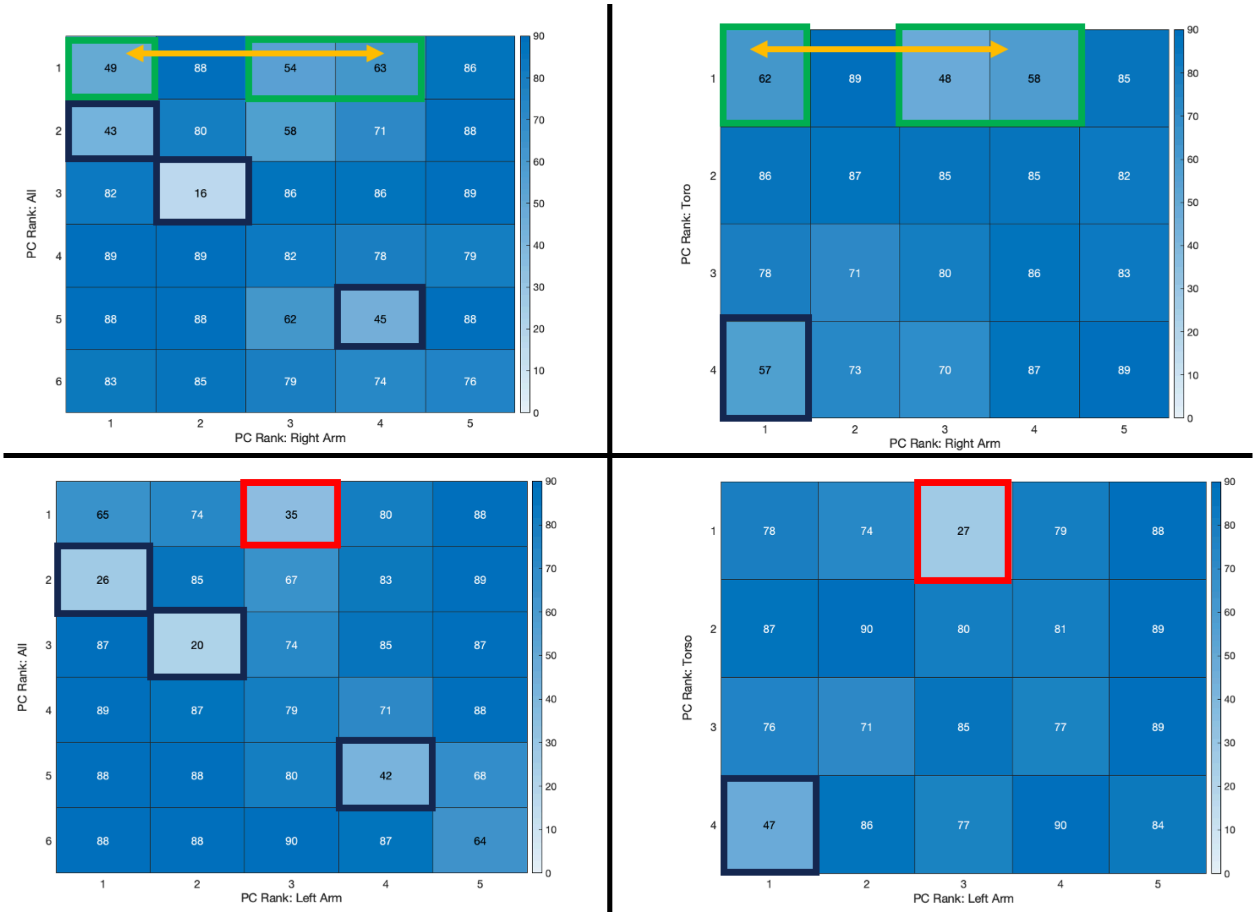
C) Participant 5



The subspace characteristics of participants 1, 3 and 5 demonstrate that functional subspace identification is useful for identifying coordination characteristics related to the independence of functional groups that can be used to identify asymmetries in arm movements during the performance of symmetrical tasks. It should be noted that although these three participants were all included in the asymmetrical category, they had different asymmetrical subspace characteristics in relation to one another. Participant 1 displayed the greatest degree of independence between the torso and the arms, and the greatest independence between the right and left arm. Participant 3 displayed overall more symmetrical arm movement compared to participant 1, but still had clearly identifiable unique right-arm subspaces pointing to unique right arm movement characteristics that distinguish its variation from the left arm. Participant 3 also had asymmetrical subspaces relating the arms to the torso, with the left arm showing evidence of coordination with the torso and the right arm displaying variation independent of the torso. Like participant 3, participant 5 displayed asymmetries in arm coordination with the torso, with the left arm showing evidence of coordination with the torso and the right arm varying independently of the torso. Although this was the only obvious difference in subspace characteristics in the right and left side for participant 5, the fact that the differences were found in relationships involving $PC1^{all}$ suggests that this asymmetry is visible in the PCs contributing the largest percentage of overall variance to the data set and is therefore an important participant-specific feature of their coordination for this task. A review of trials two and three revealed that many of the asymmetrical characteristics noted in trial one were consistent across trials two and three for these three participants. Future work could develop protocols for establishing the consistency of subspace characteristics across multiple trials.

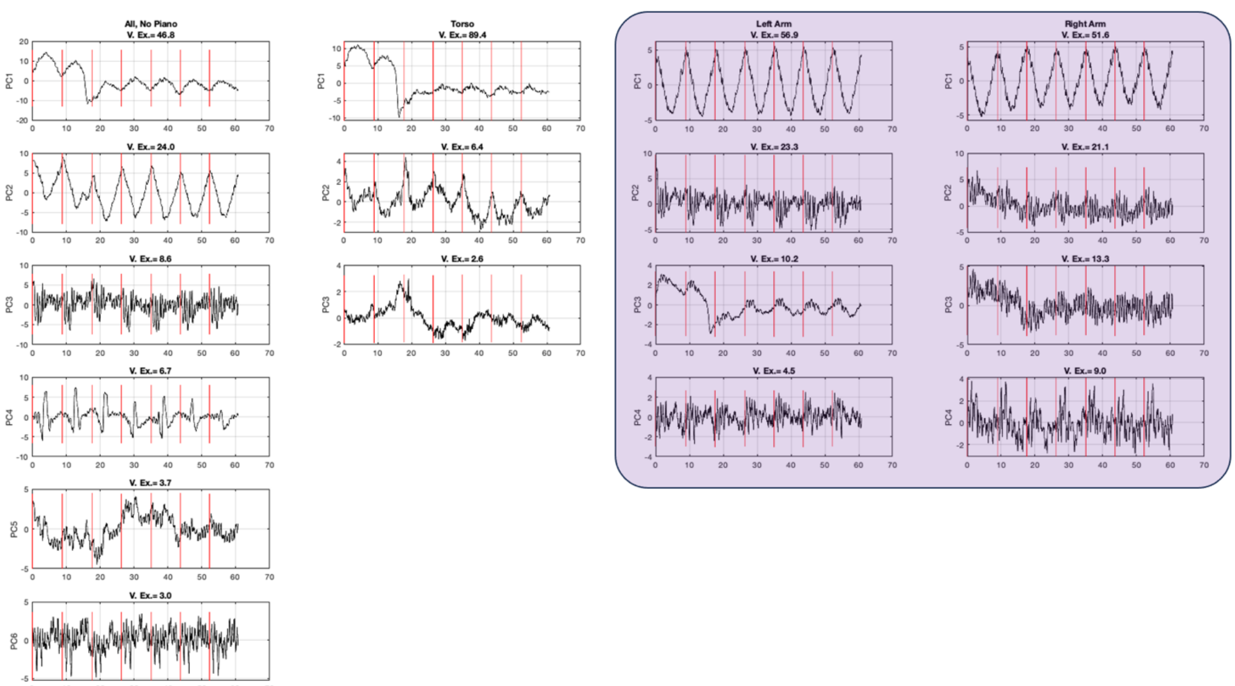
7.4.2.1.3 Contrary Motion Scales with Symmetrical and Asymmetrical Features.

Functional subspace identification identified both symmetrical and asymmetrical subspace characteristics from participant 6's contrary scales, making it difficult to classify this participant in one category or the other. Figure 7.26 displays the PC waveforms of participant 6's contrary motion scales and figure 7.27 presents the corresponding PC subspace identification map comparing the right and left arm. The PC subspace identification map in figure 7.27 show right arm and left arm subspaces for PCs 1 to 3: $PC1^{left} \approx PC1^{right}$ [14 degrees], $PC2^{left} \approx PC2^{right}$ [44 degrees] and $PC3^{left} \approx PC3^{right}$ [43 degrees]. The relationship between $PC4^{left} \approx PC4^{right}$ is the weakest at 60 degrees, but it still may indicate a subspace since it is the lowest inter-PC angle for any PC pair including $PC4^{right}$ or $PC4^{left}$. These pairwise relationships suggest that the variance of the right arm and left arm data can be represented with a similar set of PCs and likely reflect movements with symmetrical coordination characteristics for each arm.

However, it appears that the left arm has multiple distinct PC subspaces with respect to PCA^{all} and PCA^{torso} that are not replicated in the right arm, highlighted by the red squares in the lower left and lower right quadrants of figure 7.28. By contrast, the right arm PCs share weaker inter-PC angles distributed between multiple pairs over a range of PCs in PCA^{all} and PCA^{torso} (see the green rectangles and yellow arrows in the upper left and right quadrants of figure 7.28). The black rectangles in figure 7.28 show that the right and left arm share two common subspaces with PCA^{all}: $PC2^{all} \approx PC1^{left}$ [29 degrees] and $PC2^{all} \approx PC1^{right}$ [38 degrees], as well as by $PC6^{all} \approx PC4^{left}$ [49 degrees] and $PC6^{all} \approx PC4^{right}$ [36 degrees]. This suggests that the variance described by $PC2^{all}$ and $PC6^{all}$ are related to variation in the arms, but not unique to the right or left arm, and likely reflect symmetrical features of the arm movements. However, the red squares in the lower-left quadrant of figure 7.28 highlight left arm specific subspaces represented by the pairs $PC3^{all} \approx PC2^{left}$ [26 degrees] and $PC1^{all} \approx PC3^{left}$ [31 degrees]. A left arm specific subspace is also represented by the pair $PC1^{torso} \approx PC3^{left}$ [21 degrees], highlighted by the red square in the lower right-hand quadrant of figure 7.28. Figure 7.29 shows that $PC1^{torso}$ relates strongly with $PC1^{all}$ [15 degrees]. The strong relationships represented by the pairs $PC1^{all} \approx PC1^{torso}$ [15 degrees] and $PC1^{torso} \approx PC3^{left}$ [21 degrees] suggests that part of the left arm variation coordinates strongly with the torso. The green rectangles and yellow arrows in the upper-left and right quadrants of figure 7.28 show that much of the right arm variation is distributed over several PC pairs in PCA^{torso} and PCA^{all}, suggesting the right arm movements are coordinated more broadly across the subgroups. Taken together, these observations suggest that the coordination characteristics of participant 6’s right and left arms are somewhat symmetrical, but the left arm is more strongly related to the torso compared to the right arm. Participant 6’s subspace characteristics share the symmetrical right and left arm PCs displayed by participants 2 and 4, but also display asymmetries in how the right and left arm coordinate with the torso, as was evident in participants 3 and 5. These subspace characteristics remained consistent throughout trials two and three for participant 6.

Figure 7.26

PC Waveforms ≥ 2% Variance for Participant 6, Contrary Scales, Trial 1



Note. The purple-coloured blocks highlight PC subspaces between PCA^{left} and PCA^{right}. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

Figure 7.27

PC Subspace Identification Maps Comparing Right and Left Arm PCs for Participant 6, Contrary Scales, Trial 1

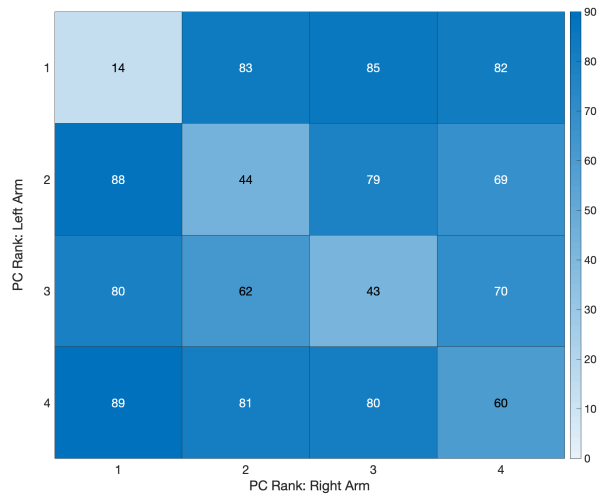


Figure 7.28

PC Subspace Identification Maps Comparing Each Arm with Torso and All PCs for Participant 6, Contrary Scales, Trial 1

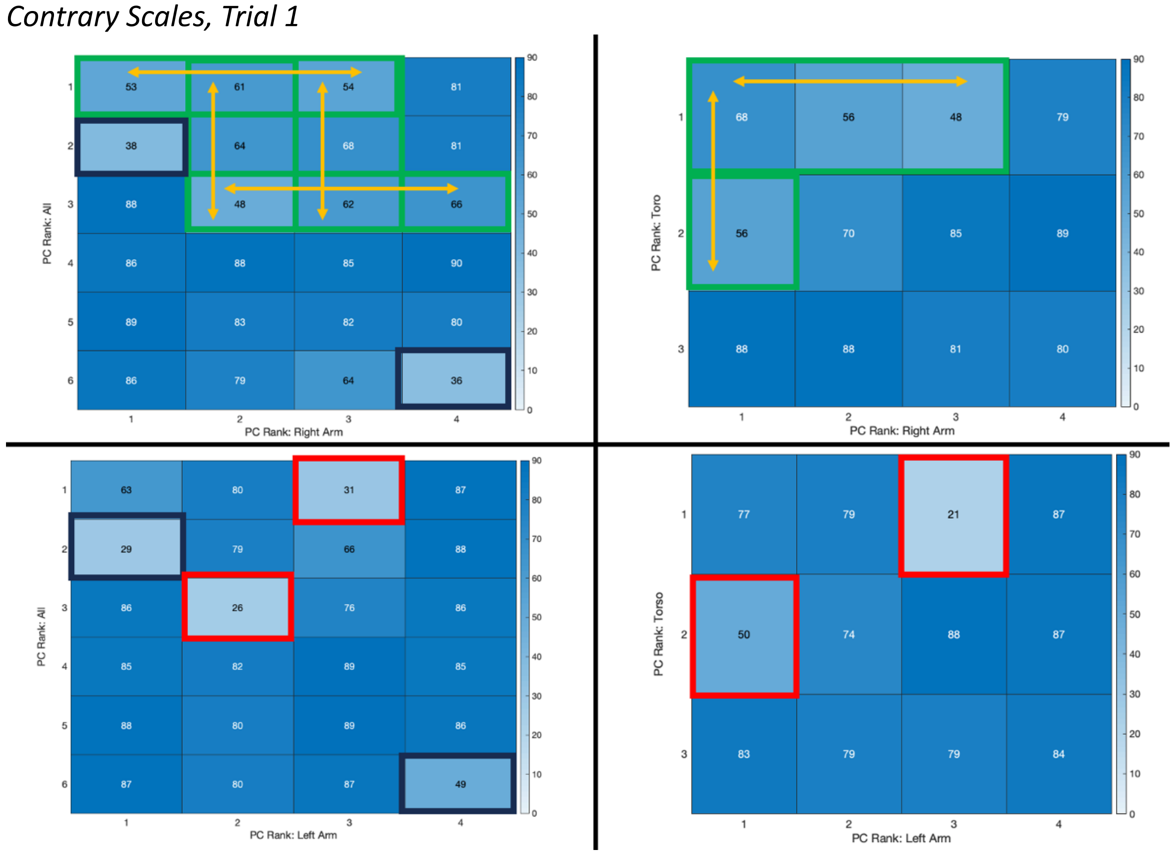
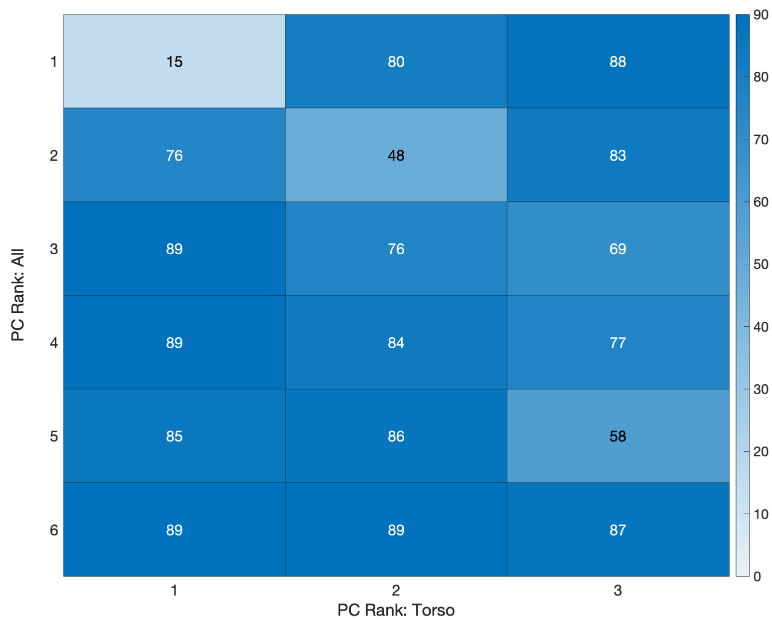


Figure 7.29

PC Subspace Identification Maps Comparing All and Torso PCs for Participant 6, Contrary Scales, Trial 1



7.4.2.1.4 Accounting for Asymmetries in Contrary Scale Performances.

Comparing the characteristics of the one-dimensional PC subspaces across PCA^{all} and PCAs from the right arm, left arm, and torso subgroups helped identify coordination characteristics in the performances of contrary scales that allowed participants to be broadly categorized according to whether their performances were best described as symmetrical or asymmetrical. Beneath those broad categorizations, each participant had unique variation characteristics resulting in unique subspace features. In its present form, functional subspace identification can help identify groups of markers implicated in the variation patterns linked with differences between the arms, but they cannot identify specific movement features linked to specific joints. However, using visual inspection, the interpretations of the PC subspaces characteristics as indicators of symmetrical versus asymmetrical arm movements appear to be supported by raw motion capture trajectory plots of the contrary motion scale performances. Figure 7.30 displays selected motion capture trajectory plots of variables illustrating existing asymmetries in the arm movements of participants 1, 3, 5, and 6 which may partially account for the asymmetrical subspace characteristics discovered in the functional subspace identification. It must be emphasized that the visual examination of the 3D and 2D plots of raw motion capture variables presented below are intended to facilitate discussion of possible relationships between specific movements and the resulting PC subspaces and not to make quantitative assessments of the raw data. The purposes of these observations to stimulate the discussion of possible future research steps that may help link PC subspaces to biomechanically identifiable features.

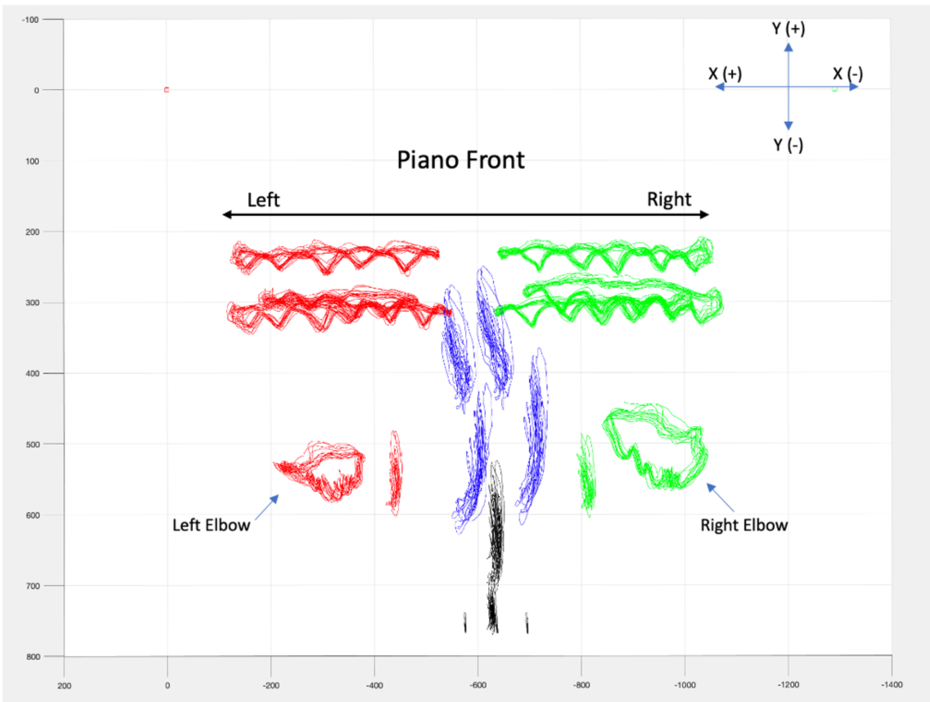
In the case of participant 1, visual inspection of the trajectories in figure 7.30(A) inspection shows that the greatest difference in their right and left arms was in the range of motion and trajectory shape for the y-axis elbow. Although less prominent, the right ulna also displayed a greater y-axis range of motion compared to the left ulna, with slightly different shapes in each cycle. For participant 3, the bold boxes in figure 7.30(B) highlight subtle differences in the trajectory shapes of several of the arm trajectories in the y- and z-axes. For example, the z-axis trajectory of the left elbow has a greater range of motion than the z-axis trajectory of the right elbow for participant 3. Also, the z-axis trajectories of the left ulna, metacarpophalangeal joint (MCP), radius, and acromion all have a more prominently cyclical increase and decrease aligning with task repetitions marked by the vertical red lines compared to the corresponding variables on the right side. Participant 5 exhibits differently shaped movement in the right and left elbow, which is visible in the top view trajectory plot in figure 7.30(C), and in the right and left plots of elbow trajectories in the y- and z- axes. Like participant

3, participant 5's left MCP and radius appear to vary more cyclically with task repetitions on the left side compared to the right in the z-axis. The differences between the right and left arm are subtler and less apparent to the naked eye for participant 6. However, the black boxes in figure 7.30(D) highlight that many z-axis variables contain slight differences in shape and frequency content between the right and left side. Of note is the difference in the z-axis of the left and right acromion. The z-axis of the right acromion has a sudden shift downward just before the beginning of the third task repetition which temporally aligns with a sudden increase in the y-axis of the left and right acromion. However, although present in the y-axis of the left acromion, this sudden shift is absent in the z-axis of the left acromion, which continues moving cyclically with the task in the same manner for the duration of the trial. This suggests that at that moment in the trial both shoulders moved forward toward the keyboard (positive shift in the y axis), and the right shoulder slid down slightly (negative shift in the z axis) staying lower for the rest of the trial. However, the left shoulder continued moving up and down in the z-axis cyclically, uninterrupted by the y-axis shift forward.

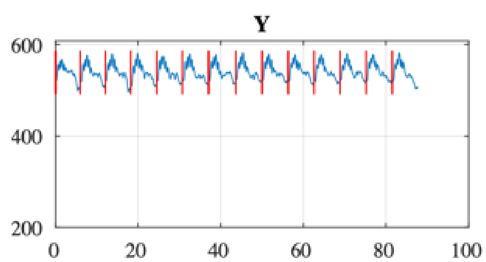
Figure 7.30

Selected Motion Trajectories Highlighting Asymmetries of Right and Left Arm Movement in Contrary Motion Scales, Participants 1, 3, 5 and 6, Trial 1

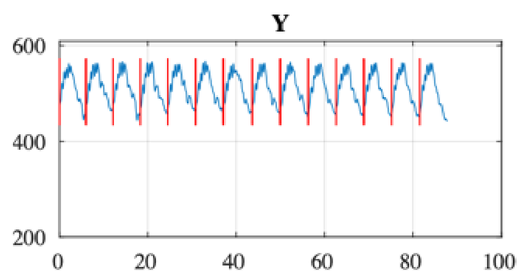
A) Participant 1 -Top View and Elbow/Ulna Plots in the Y-Axis



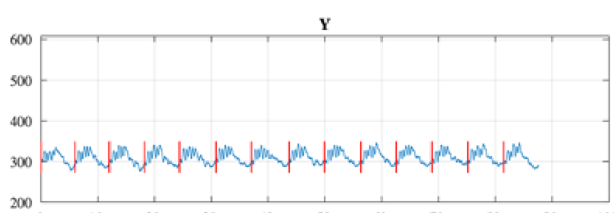
Left Elbow, Y



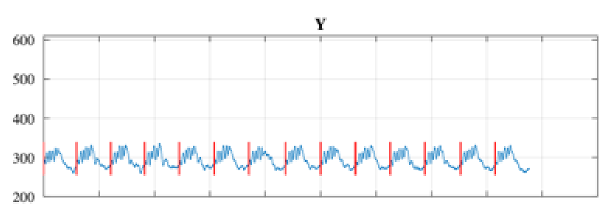
Right Elbow, Y



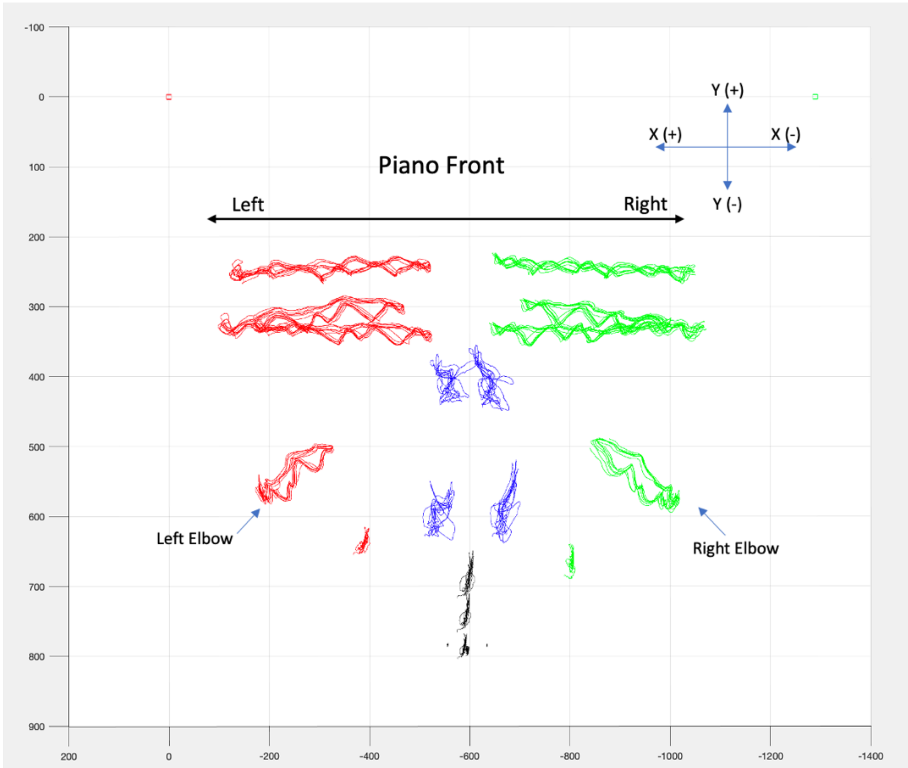
Left Ulna, Y



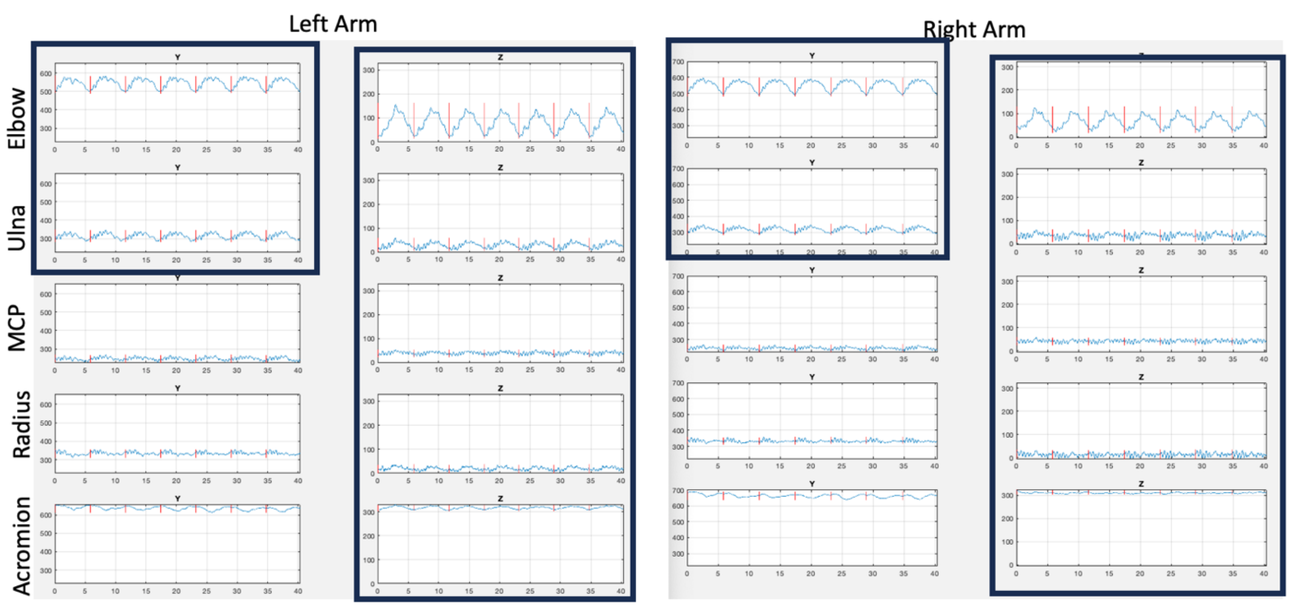
Right Ulna, Y



B) Participant 3-Top View and Arm Trajectories in the Y- and Z-axes



Y & Z Trajectories of Participant 3's Arms, Contrary Scales, Trial 1



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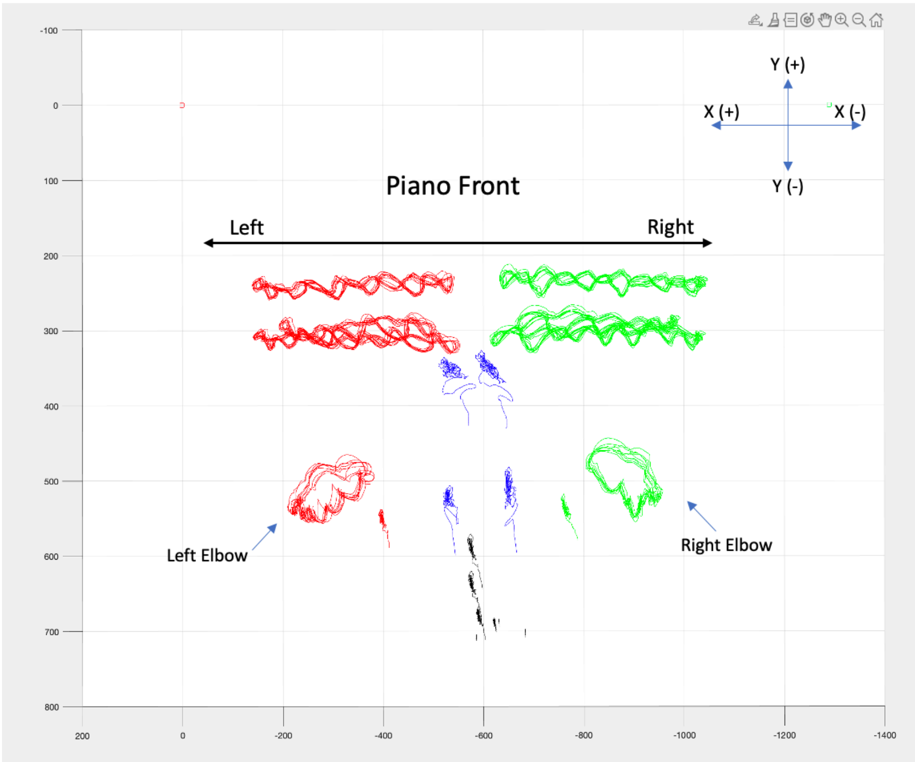
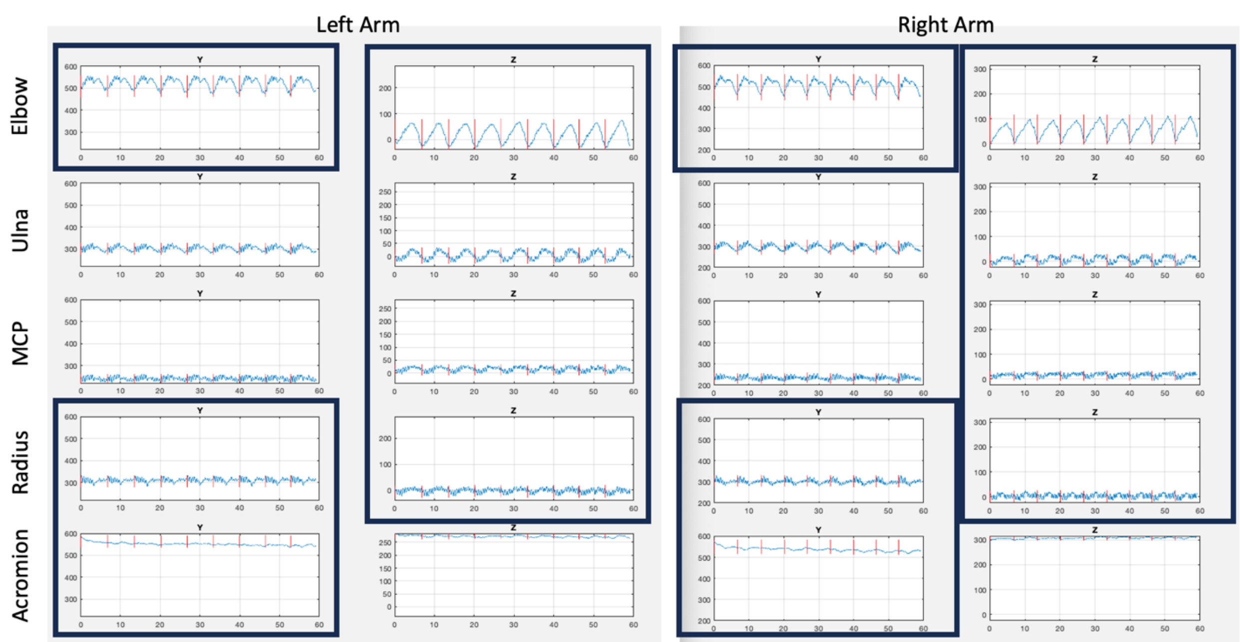
C) Participant 5-Top View and Arm Trajectories in the Y- and Z-axes



Y & Z Trajectories of Participant 5's Arms, Contrary Scales, Trial 1



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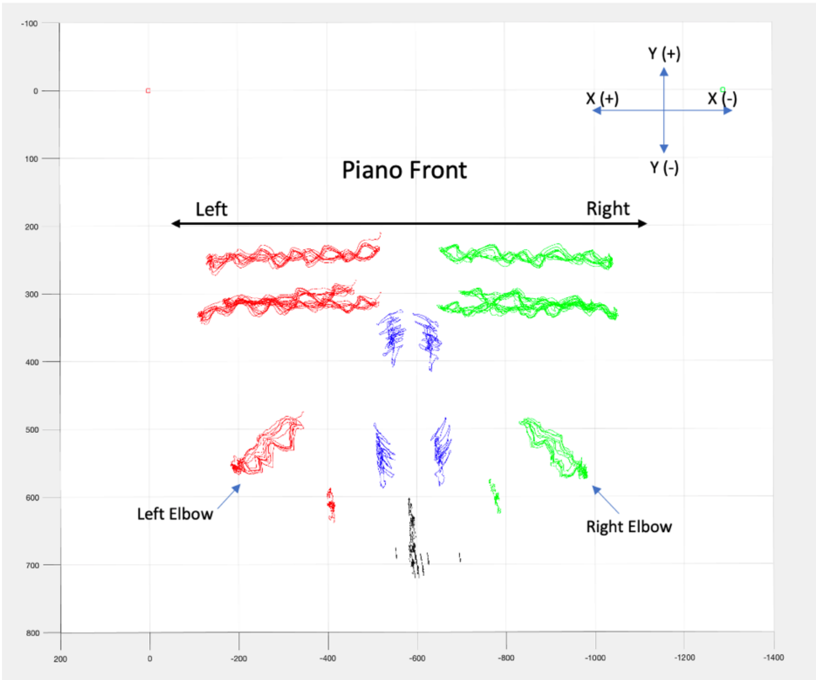
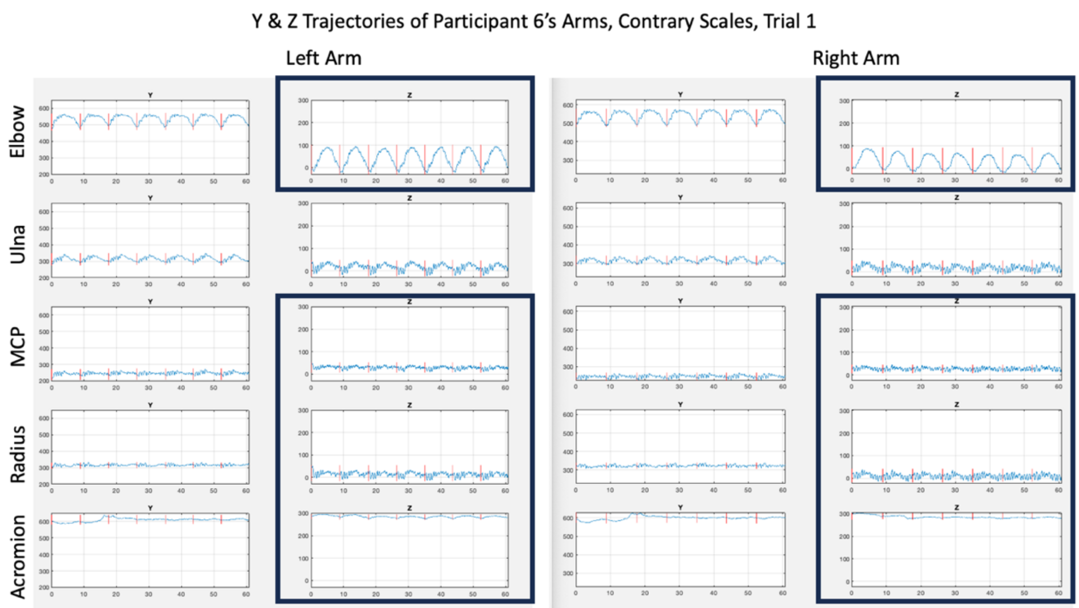
D) Participant 6- Top View and Arm Trajectories in the Y- and Z-axes





Note. For the top view motion trajectory plots, blue trajectories correspond to head markers. Black trajectories correspond to spine and pelvic markers. Green markers correspond to the right arm and shoulder markers. Red markers correspond to the left arm and shoulder markers. Black rectangles highlight trajectories with visible differences in the right and left arms. For individual motion trajectory plots the x-axis is time in seconds and the y-axis is in mm.

Interestingly, three of the four participants with prominent asymmetrical features in their scale playing reported experiencing chronic playing-related arm pain. Participant 1 reported chronic left shoulder and C7/T1 nerve pain associated with piano practice. The first onset of the pain was in 2009 and the participant continues to manage the symptoms by incorporating somatic training modalities and stretching into their daily practice routines. Participant 5 reported ongoing playing related pain in both the left and right wrist which occasionally prevented them from playing the piano. Their pain is aggravated by long or intense piano practice sessions or by doing weight bearing exercises with the arms. They manage symptoms by exploring different practice strategies and different styles of somatic training. Although participant 6 presented with both symmetrical and asymmetrical subspace characteristics, they did report recent onset of pain and fatigue beneath the left scapula and between the left scapula and the spine which typically appeared around the second or third hour of practice sessions. Interestingly, it was their shoulder movements that showed the greatest difference in the right and left side when looking at the raw movement trajectories. Participant 2 was classified as an asymmetrical player but reported no history of playing-related pain.

One of the symmetrical players (participant 4) did not report any history with playing-related pain or discomfort. However, the other symmetrical player (participant 2) reported an onset of tendinopathy in both arms in 2014 that had since resolved after studying the Taubman Technique, a form of somatic training specific to pianists aimed at preventing or reducing-playing related pain by introducing ergonomic piano playing techniques (Smith, 2012). They reported that playing-related pain rarely bothered them at the time of study. Although the sample size is too small to draw conclusions, a possible relationship between playing-related pain and asymmetrical coordination characteristics during symmetrical playing tasks should be investigated in future research. It is possible that asymmetrical arm movement characteristics may be more common in players experiencing unilateral playing-related pain compared to those who do not experience it.

7.4.2.1.5 Summary of Results on Participant-Specific Subspaces in Symmetric Scales.
The results from the symmetric contrary scales task demonstrates that the strategy of functional subspace identification can effectively identify differences in coordination characteristics between the right and left arm in tasks with identical biomechanical and musical task parameters for each hand. By comparing PCs of the right and left arm we were able to determine that subspace characteristics pertaining to arm independence and arm and torso independence were highly symmetrical for some of the participants, while others exhibited unique variation characteristics particular to the right and left arm. In the future, functional subspace identification could be applied to other symmetric tasks from the battery of musical tasks, such as the symmetric blocked 5ths, or the Alberti Bass pattern, to determine whether individual tendencies to play symmetric tasks with asymmetrical movement strategies persists across tasks or is specific to particular tasks. Future research could apply the strategy to a greater number of participants to investigate if there is a relationship between playing-related pain and asymmetrical arm movements in symmetric playing tasks, or if somatic training impacts symmetry in pianists' arm movements. Although functional subspace identification can give an indication of differences in coordination characteristics between the right and left hand,

at present it cannot be used to identify specific movement characteristics that differ in the right and left arms.

7.4.2.2 Results Part II (b): Using PC Subspaces to Identify Participant-Specific Coordination Characteristics for Tasks Requiring Hand Displacement in the X-Y Plane of the Keyboard. The piano keyboard is composed of a repeating sequence of seven longer white keys, and five shorter and elevated black keys arranged in alternating groups of two and three. Playing the black keys with the shorter fingers (thumb and pinky) requires pianists move their hand forward in the y-axis. Therefore, as pianists play, they must find strategies for coordinating the torso and arms so that they can successfully navigate horizontal hand displacement along the keyboard (x-axis), and forward and backward displacement along the length of the keys (y-axis).

We were interested to find out whether the PC subspace comparison strategy could be useful for identifying pianist-specific coordination characteristics in a task requiring pianists' hands to travel to the extreme ends of the keyboard along the x-axis while also moving forward and backward along the keys in the y-axis. Toward this end, we devised a whole-tone blocked octave scale task that would require pianists to move their hands forward and backward in the y-axis to target alternating groups of white keys and black keys (figure 7.31). This task requires pianists to play blocked octaves with their first and fifth fingers (thumb and pinky) with their right and left hands simultaneously. They perform a repeated pattern of notes alternating between three successive white keys (C-D-E) and three successive black keys (G♭-A♭-B♭).

Figure 7.31

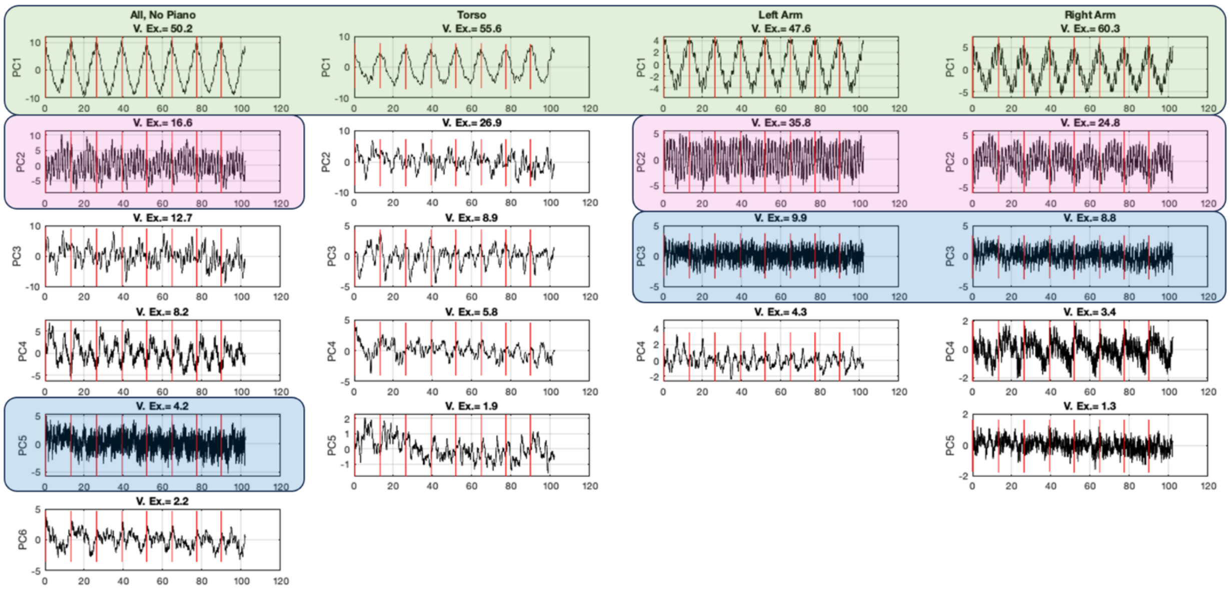
Whole Tone Blocked Octave Scale Task

There are several possible strategies for coordinating the arms and torso to reach the extreme ends of the keyboard and for moving the hands forward and backward along the y-axis. For instance, some pianists rely predominantly on arm movements to reach extremes of the x- and y-axes, such as extending and flexing the elbow joints. Others may assist the arm in reaching by incorporating movements of the torso, such as flexing and extending the spine, turning the spine and shoulders, translating the spine from left to right, or rocking on the pelvis. We hypothesized that it would be possible to find evidence of pianist-dependent arm and torso coordination characteristics for the blocked octave task by studying PC subspaces of tasks requiring significant x-axis displacement (displacement horizontally along the keyboard).

An initial survey of the PC subspace characteristics of the blocked octaves task using the inter-PC angles in the PC subspace identification maps revealed subspaces common to all participants and consistent across trials, suggesting that a significant proportion of the overall variance was task-determined. As occurred in the previously discussed tasks, PC1 formed a common subspace across PCA^{all}, PCA^{torso}, PCA^{left} and PCA^{right}, as highlighted by the green-coloured block in of the example waveforms in figure 7.32. However, we also observed that PC2 and PC3 of both PCA^{left} and PCA^{right} displayed distinctive waveform characteristics related to the musical pattern and formed subspace pairs $PC2^{left} \approx PC2^{right}$ and $PC3^{left} \approx PC3^{right}$ for all participants. Furthermore, PC2 and PC3 from the arms formed unique, independent subspaces with respect to PCA^{all} for all participants. In most cases, $PC2^{all}$ formed subspaces with both $PC2^{left}$ and $PC2^{right}$ and $PC5^{all}$ formed subspaces with both $PC3^{left}$ and $PC3^{right}$ as highlighted by the fuchsia- and blue-coloured blocks in figure 7.32. For participants 4 and 6, $PC2^{left}$ and $PC2^{right}$ related to $PC3^{all}$ instead of $PC2^{all}$, and for participants 5 and 6, $PC3^{left}$ and $PC3^{right}$ related to $PC4^{all}$. In all cases, these two waveforms represented independent variation patterns existing in both arms and identifiable as a subspace in PCA^{all}. This suggests that for this task, PC1, PC2, and PC3 of the arm PCAs were strongly driven by task-determined variation and only PCs numbered four or higher would relate to participant specific variation in the arm PCAs. These characteristics were first identified by comparing inter-PC angles in PC subspace identification maps (not shown in the following figures) and then cross referencing with the PC waveforms (shown for reference below).

Figure 7.32

An Example of Task-Determined Subspaces Related to Arm PCs in Blocked Octaves, Participant 1, Trial 1

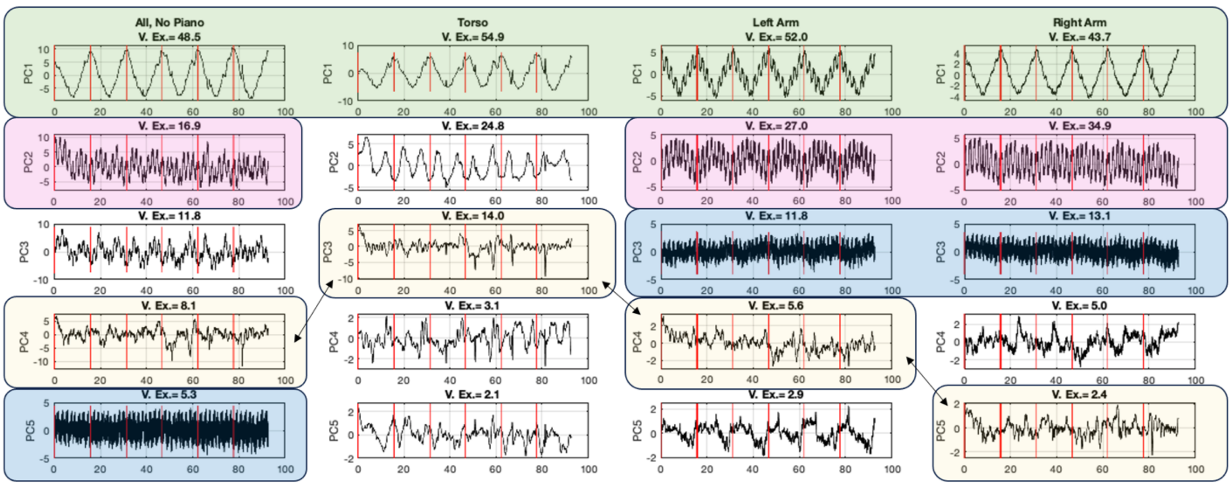


Note. The green-coloured block highlights PC1 commonalities across all PCAs. The pink-coloured blocks highlight the subspace created by $PC2^{arms}$ and $PC2^{all}$. The blue-coloured blocks highlight the subspace created by $PC3^{arms}$ and $PC5^{all}$. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

Although a great deal of the variation represented by the first three arm PCs likely relates to task-determined variation consistent across participants, conducting functional subspace identification across the six pianists revealed examples of participant-specific characteristics for coordinating the torso and arms during the blocked octave task. For instance, participant 2 exhibited unique PC subspace relationships between the arm and torso. In their case, $PC4^{left}$ and $PC5^{right}$ appeared to relate to $PC3^{torso}$ and $PC4^{all}$, as highlighted in the yellow-coloured blocks in figure 7.33. The inter-PC angles for each subspace pair are found in table 7.6. These relationships suggest that the right and left arm were coordinated with the torso for some aspects of participant 2's movement. Since the inter-PC angles are lower for left-arm comparisons than the right-arm comparisons (left side comparisons are marked with asterisks in table 7.6), it may be that the coordination relationships between the left arm and the torso is stronger than that of the right arm and the torso.

Figure 7.33

Participant-Specific and Task-Determined PC Subspaces for Blocked Octave Task, Participant 2, Trial 1



Note. The green-coloured block highlights PC1 commonalities across all PCAs. The pink-coloured blocks highlight the subspace created by $PC2^{arms}$ and $PC2^{all}$. The blue-coloured blocks highlight the subspace created by $PC3^{arms}$ and $PC5^{all}$. The yellow-coloured blocks highlight a participant-specific PC subspace common to all PCAs. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

Table 7.6

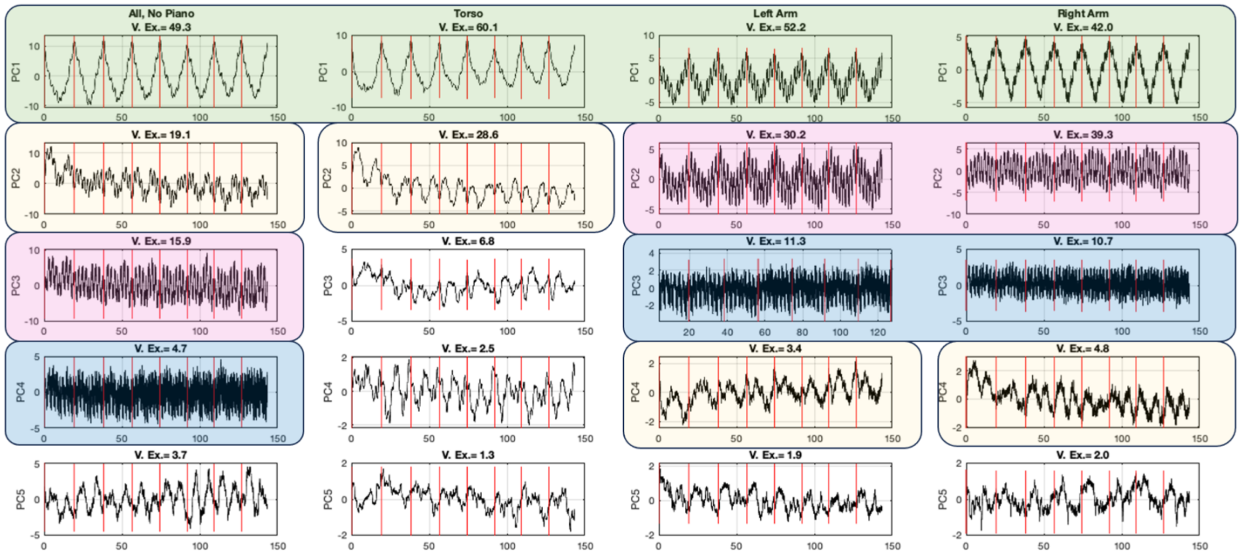
Inter-PC Angles in Subspace Pairs for Participant-Specific Subspace Relating the Arms and Torso, Participant 2, Trial 1

PC Pair	Inter-PC Angle (degrees)
$PC4^{left} \approx PC5^{right}$	62
$PC3^{torso} \approx PC4^{left}$	47*
$PC3^{torso} \approx PC5^{right}$	51
$PC4^{all} \approx PC3^{torso}$	27
$PC4^{all} \approx PC4^{left}$	46*
$PC4^{all} \approx PC3^{right}$	59

Similarly, participant 6 exhibited evidence of coordination between the torso and both arms. In this case, $PC4^{left}$ and $PC4^{right}$ appeared to relate to $PC2^{torso}$ and $PC2^{all}$, as highlighted in the yellow-coloured blocks in figure 7.34. The inter-PC angles for each subspace pair are found in table 7.7. In this case, the inter-PC angles for right arm and left arm comparisons with PCA^{torso} and PCA^{all} are almost identical, so it is likely that the right and left arm coordinated more similarly with the torso for participant 6 than for participant 2.

Figure 7.34

Participant-Specific and Task-Determined PC Subspaces for Blocked Octave Task, Participant 6, Trial 1



Note. The green-coloured block highlights PC1 commonalities across all PCAs. The pink-coloured blocks highlight the subspace created by $PC2^{arms}$ and $PC2^{all}$. The blue-coloured blocks highlight the subspace created by $PC3^{arms}$ and $PC5^{all}$. The yellow-coloured blocks highlight a participant-specific PC subspace common to all PCAs. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

Table 7.7

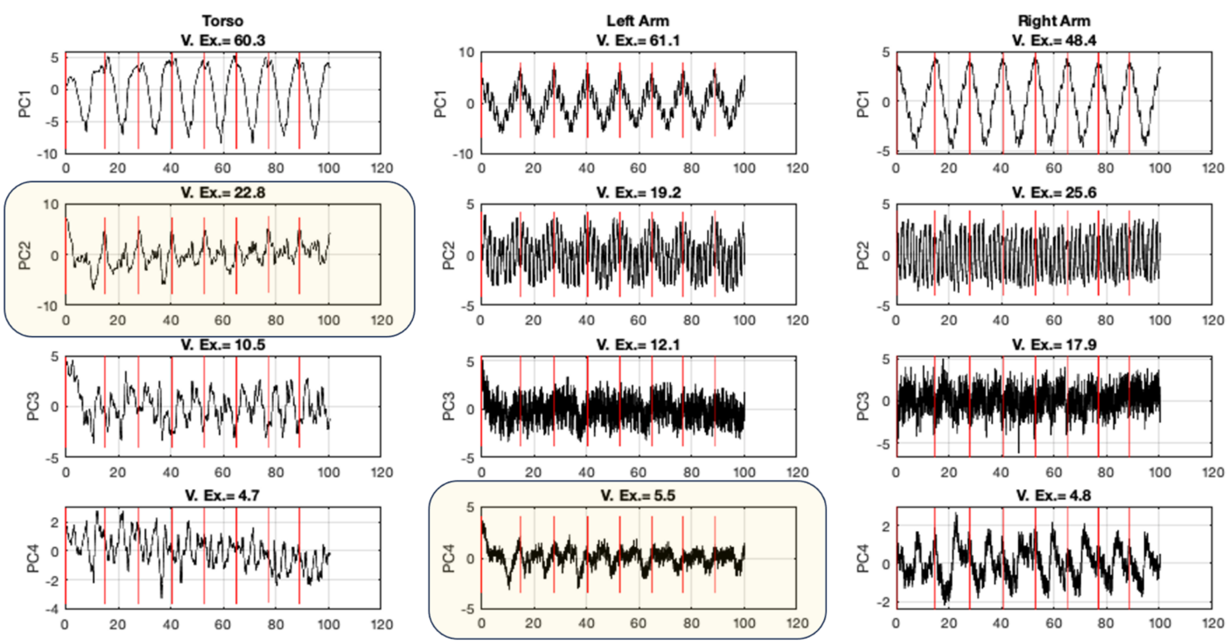
Inter-PC Angles in Subspace Pairs for Participant-Specific Subspace Relating the Arms and Torso, Participant 6, Trial 1

PC Pair	Inter-PC Angle (degrees)
$PC4^{left} \approx PC4^{right}$	59
$PC2^{torso} \approx PC4^{left}$	43
$PC2^{torso} \approx PC4^{right}$	44
$PC2^{all} \approx PC2^{torso}$	22
$PC2^{all} \approx PC4^{left}$	44
$PC2^{all} \approx PC4^{right}$	44

In the case of participant 4, only the left arm formed a subspace with the torso, while the right arm did not, as highlighted by the yellow-coloured blocks in figure 7.35. In this case, $PC2^{torso} \approx PC4^{left}$ [50 degrees]. There are no other comparably low inter-PC angles among the arm and torso PC pairs outside of the expected $PC1^{torso} \approx PC1^{arm}$ (figure 7.36). The unique subspace between the torso and the left arm may indicate that participant 4's left arm movements coordinated with the torso while the right arm moved more independently.

Figure 7.35

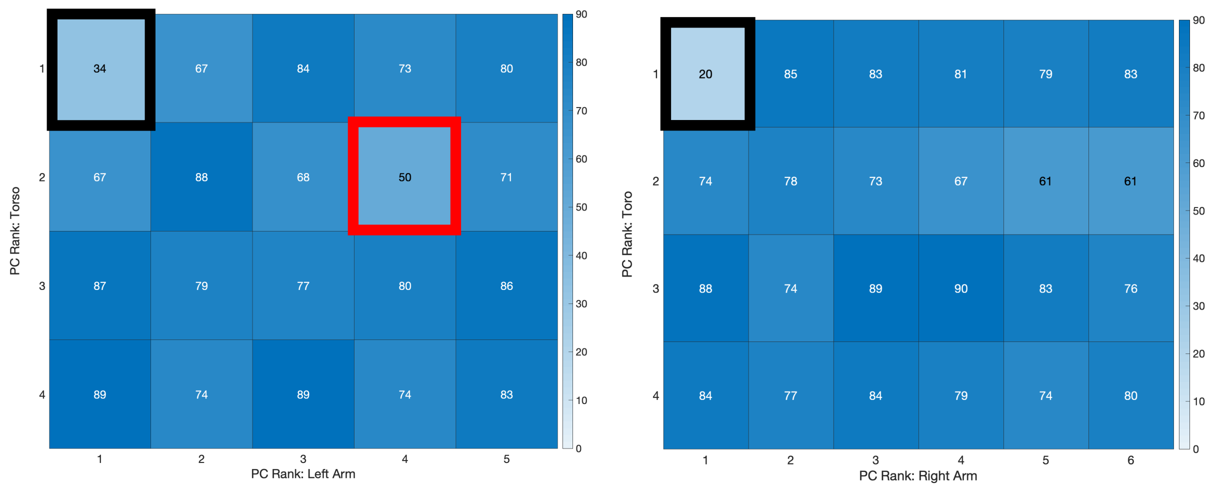
PC Subspace Unique to Left Arm and Torso, Blocked Octaves, Participant 4, Trial 1



Note. The yellow-coloured blocks highlight a participant-specific PC subspace between $PC4^{torso}$ and $PC2^{all}$. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

Figure 7.36

PC Subspace Identification Maps Comparing Arm and Torso PCs for Participant 4, Blocked Octave Scales, Trial 1

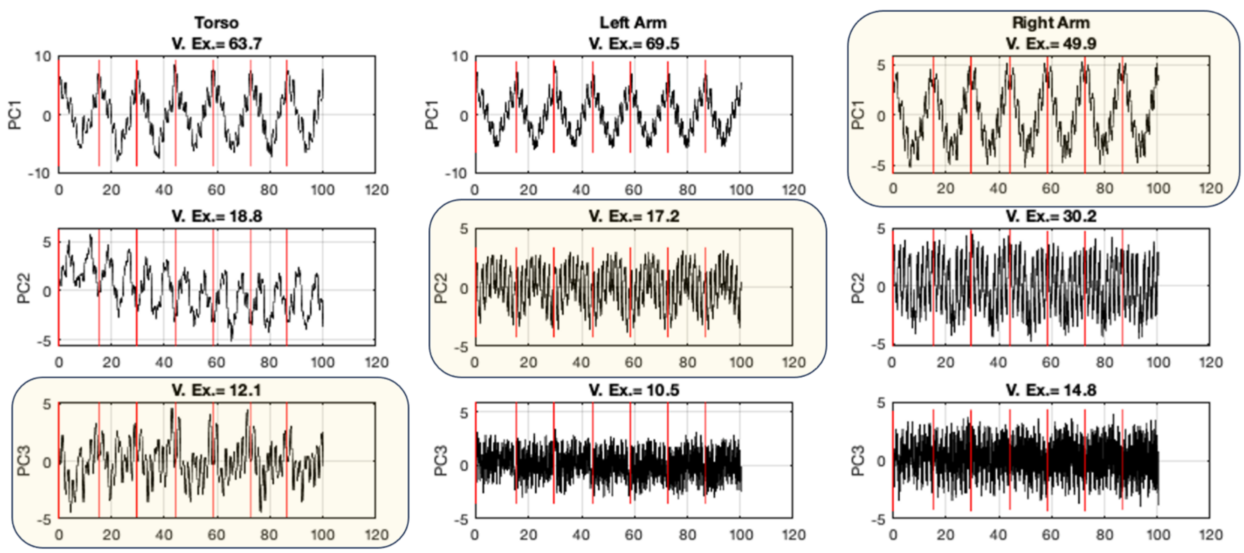


Note. The red square highlights the unique subspace relating the left arm to the torso that is not present in the right arm.

Functional subspace identification suggested that during the blocked octaves task most of the participants exhibited at least some degree of coordination between the torso and arms similar to the examples presented above. However, participant 3 exhibited a unique coordination characteristic that was not observed in any of the other participants. Participant 3 was the only participant for whom subspaces were noted between a lower-numbered, task-dependent arm PCs ($PC1^{right}$ and $PC2^{left}$) and a torso PC other than PC1 (in this case, $PC3^{torso}$), highlighted by the yellow-coloured blocks in figure 7.37. Figure 7.38 displays these unique relationships in the inter-PC angles for PC pairs between the torso and each arm. The red rectangles identify subspaces pairs $PC3^{torso} \approx PC2^{left}$ [48 degrees] and $PC3^{torso} \approx PC1^{right}$ [50 degrees]. Overall, participant 3 has lower inter-PC angles comparing torso and arms compared to other participants, especially in the case of the right arm. Most other participants exhibit strong relationships between PC1^{torso} and PC1 of each arm with one additional, weaker subspace between a higher-numbered arm PC and a torso PC other than PC1 or PC2. This unique relationship between PC1 and PC2 of the arms and PC3 of the torso suggests that an aspect of variation related to the task parameters governing hand movement is coordinated with the torso movement for participant 3 in a way that is not occurring for any other participant in this study.

Figure 7.37

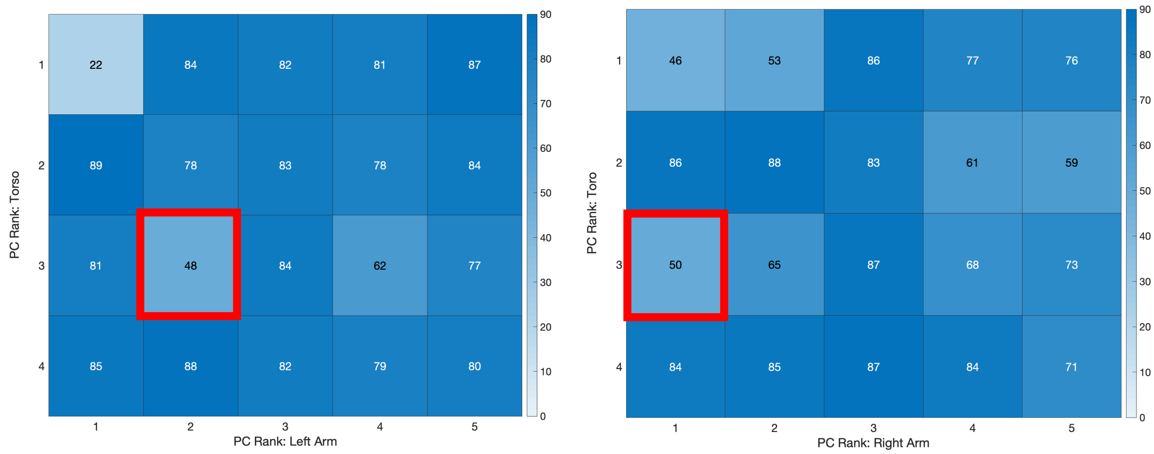
Unique Arm-Torso Subspaces from Participant 3, Blocked Octaves, Trial 1



Note. The yellow-coloured blocks highlight a participant-specific PC subspace between PC3^{torso} and PC2^{left} and PC2^{right}. The x-axis label of all PC waveform plots in this paper is time (seconds). The numbers after Ex. = indicate the percentage of total variance explained by each component.

Figure 7.38

PC Subspace Identification Maps for Torso and Arms, Blocked Octaves, Participant 3, Trial 1

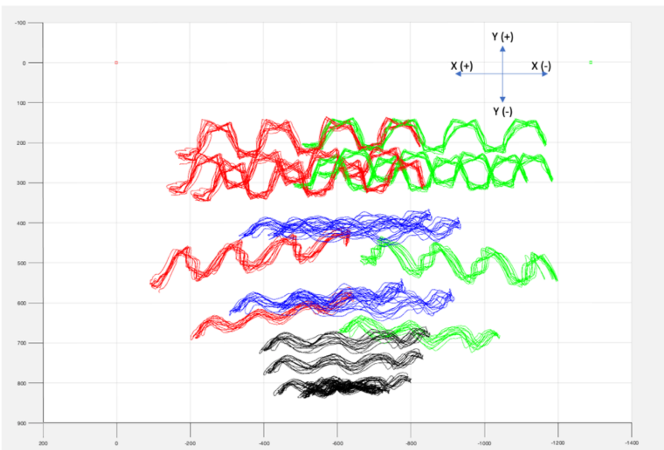


We examined motion trajectory plots of each participant's performance of blocked octave scales to look for evidence of movement differences which may account for the unique subspace characteristics exhibited by participant 3. Figure 7.39 (A) and (B) show top view motion trajectory plots from participant 3 and participant 4, respectively. Both participants exhibit similar movements of the hands and elbows in the x-y plane, characterized by an alternating shift forward and backward in the y-axis as the participants hands move horizontally in the x-axis. This pattern corresponds to the participants moving their hands forward in the y-axis to reach the group of three consecutive black keys with the thumb and pinky and then moving backward to strike the group of three consecutive white keys in the pattern. Participant 4's trajectories show that most of the movement of the head, spine, and pelvis is coordinated horizontally along the x-axis, with minimal movement forward and backward in the y-axis (figure 7.39, B). By contrast, the movement of participant 3's head, torso, and pelvis smoothly coordinate with the movement of the hands and arms, following the hands as they move forward and backward (figure 7.39, A). Participant 3 was the only participant to exhibit this coordination pattern in the x-y plane across all motion trajectories. Participant 3's unique way of coordinating the entire body with task parameters in the x-y plan may account for their unique subspace characteristics relating the arm-specific patterns in PC2^{left} and PC1^{right} with PC3 torso.

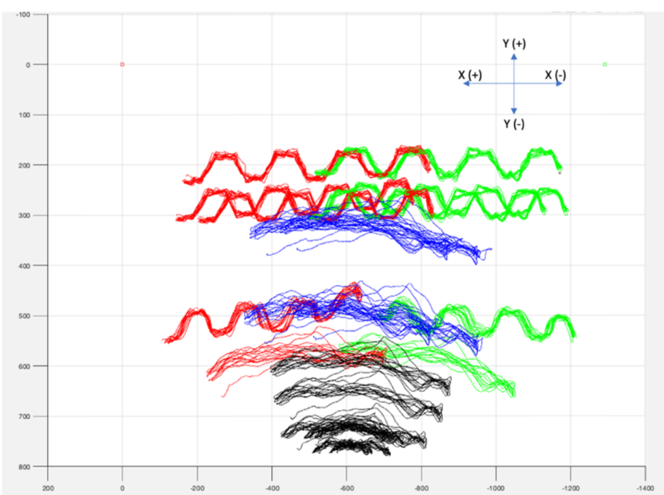
Figure 7.39

Top View Motion Trajectories of Participant 3 and 4's Blocked Octaves, Trial 1

A) Participant 3: Exhibits X-Y Coordination Across the Body (mm.)



B) Participant 4: Exhibits Independent Torso and Arm Patterns in the X-Y Plane (mm.)



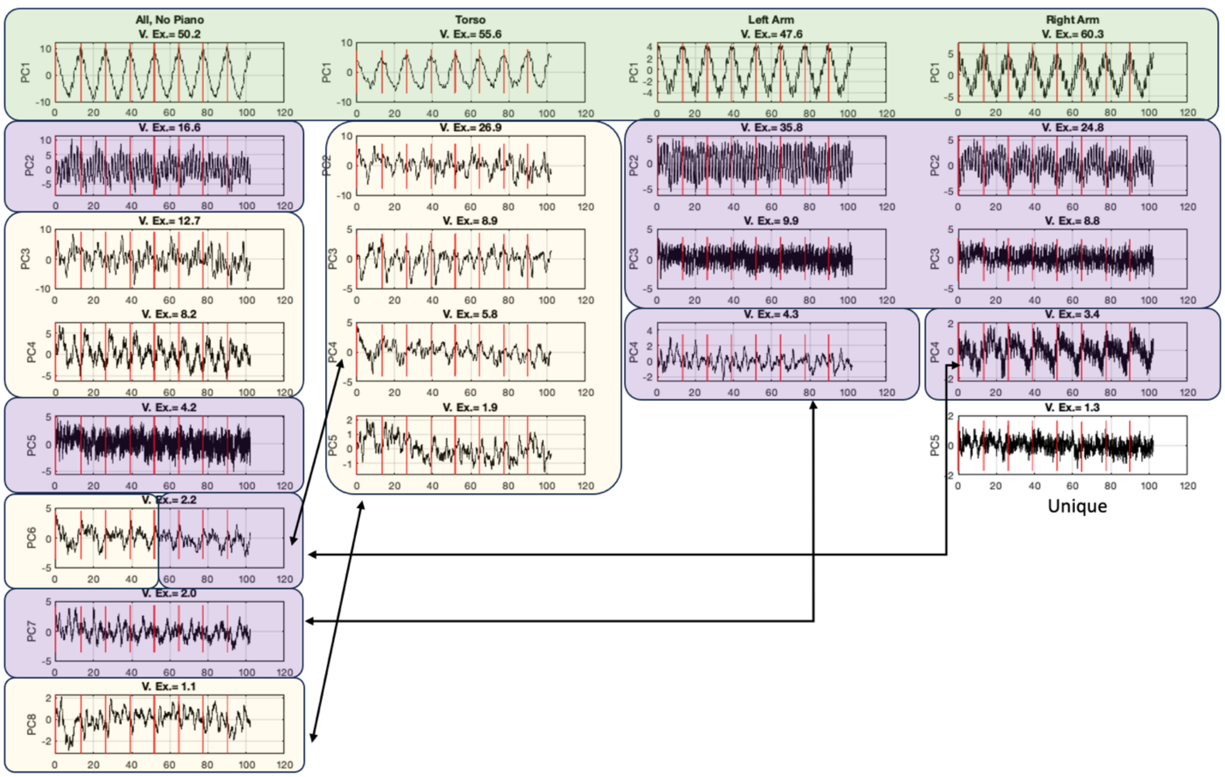
Note. Blue trajectories = head markers. Black trajectories =spine and pelvic markers. Green markers = right arm and shoulder markers. Red markers = left arm and shoulder markers.

While most of the participants in this study exhibited some evidence of torso-arm coordination for the blocked octave task, participant 1 was the only participant to exhibit highly independent movement of the torso and arms, with no subspaces between the torso and the arms evident in the arm-torso subspace identification maps. The PC waveforms in figure 7.40 show that as for the other participants, PC1 is a common subspace across all four PCAs while the PC2 of each arm relates to $PC2^{all}$, and PC3 of each arm relates to $PC5^{all}$. However, except for PC6, all other PCs from PCA^{all} relate to either a torso PC or an arm PC, but not both. This suggests that most of the PCs in PCA^{all} relate to independent subsystems of movement related to the torso and arm subgroups. Figure 7.41(A) confirms that there are no subspaces between the torso and either arm, outside of the expected PC1 similarities. In figure 7.41(B), the black rectangles marking the fourth row and fourth and fifth columns of the subspace identification map highlight an absence of subspaces between $PC4^{left}$, and $PC4^{right}$ and $PC5^{right}$, suggesting the right and left arm each have unique variation patterns that are not contained in the variation of the other. Figure 7.41(C) shows PC comparisons between the subgroups and PCA^{all}. The yellow rectangles highlight subspaces that occur in all participants and likely reflect task-determined variation. White rectangles highlight unique torso subspaces contained in PCA^{all} and the red rectangle highlights a unique left-arm subspaces in PCA^{all}. The subspaces represented by the pairs $PC8^{all} \approx PC5^{torso}$ [40 degrees] and $PC7^{all} \approx$ PC4 left arm [36 degrees] are particularly interesting because they have very low inter-PC angles, and they occur between higher-numbered PCs in their respective subgroups. This suggests that they represent independent movement variation that exists within the larger data set and that they can be linked to the movement of the specific markers included in the subgroups. Furthermore, these subspaces most likely reflect participant-specific variation patterns since they occur between higher-numbered PCs that are less associated with task-determined variation.

Interestingly, $PC5^{right}$ did not form subspaces with any other PC and appeared to be completely unique, as highlighted by the black rectangle outlining column 5 in the lower-right subspace identification map in figure 7.41(C). We hypothesized that it might be possible to find a relationship between $PC5^{right}$ and one of the PCs in PCA^{all} by reducing the variance threshold for reported PCs from 1% to 0.5%. As expected, lowering the threshold revealed a new subspace between PC5 of both the right and left arm and $PC10^{all}$, with $PC5^{left} \approx PC10^{all}$ [53 degrees] and $PC5^{right} \approx PC10^{all}$ [43 degrees]. Lowering the variance threshold also revealed a new series of subspaces relating $PC3^{all}$ to $PC6^{left}$, $PC6^{right}$, and $PC2^{torso}$. These relationships are highlighted by the orange rectangles in figure 7.42. PC6 of the right and left arms account for less than one percent of the overall variance of their respective subgroups ($PC6^{left}$ = 0.78 % of the left arm variance and $PC6^{right}$ = 1.0 % of the right arm variance). However, they share a subspace with $PC3^{all}$, which accounts for 12.0% of the overall variance of the entire data set and relates strongly with $PC2^{torso}$, which accounts for 27.0% of the variation of the torso subgroup. This suggests that the variation represented by $PC6^{left}$ and $PC6^{right}$ is related to real movements, and not just random noise, even though they account for a very low percentage of variation within their own arm subgroups. This example shows how PC subspace comparisons are sensitive to user-determined settings, such as the percent of variance considered relevant in PC subspace comparisons. It is important to consider that although higher-numbered PCs account for a much lower percentage of the overall variance, they likely contain the most information about participant-specific variation outside of task requirements. Unfortunately, the information they contain is often outsized by the dominance of task-determined variation in the earlier PCs. Furthermore, as the percentage of variance PCs describe becomes smaller, it becomes increasingly difficult to determine whether their variation is related to real patterns in the movement or random variation due to experimental noise.

Figure 7.40

PC Waveforms, Blocked Octaves, Participant 1, Trial 1

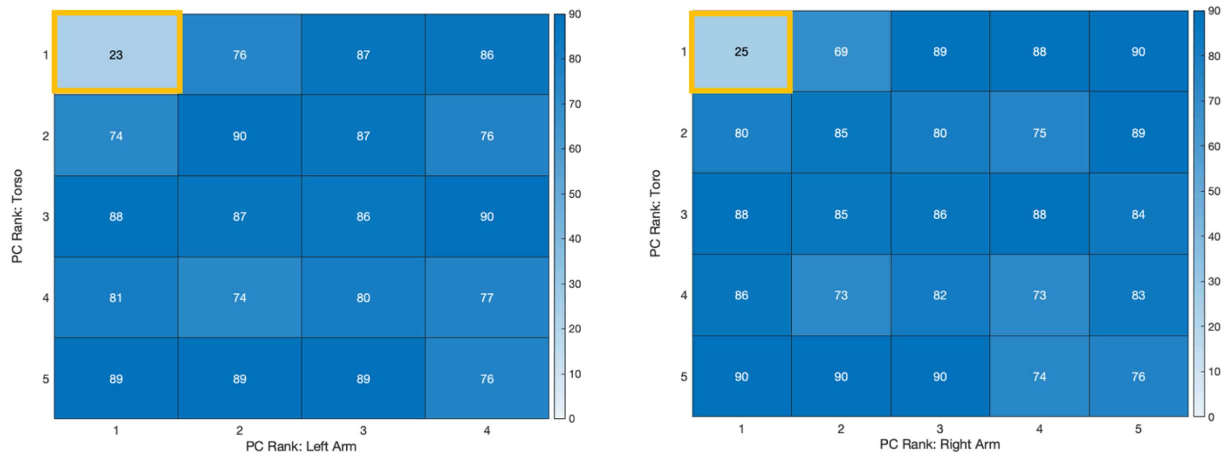


Note. The green-coloured blocks highlight the PC1 subspace common to all groups. The purple-coloured blocks highlight subspaces common to PCA^{arms} and PCA^{all}. The yellow-coloured blocks highlight common subspaces between PCA^{torso} and PCA^{all}.

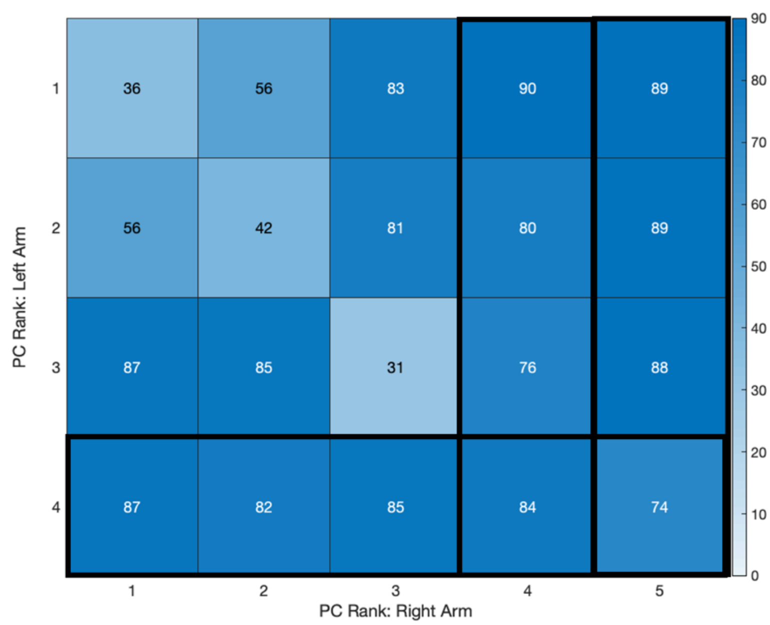
Figure 7.41

PC Subspace Identification Maps Unique Arm Subspaces, Blocked Octaves, Participant 1, Trial 1

A) Torso and Arm Comparisons

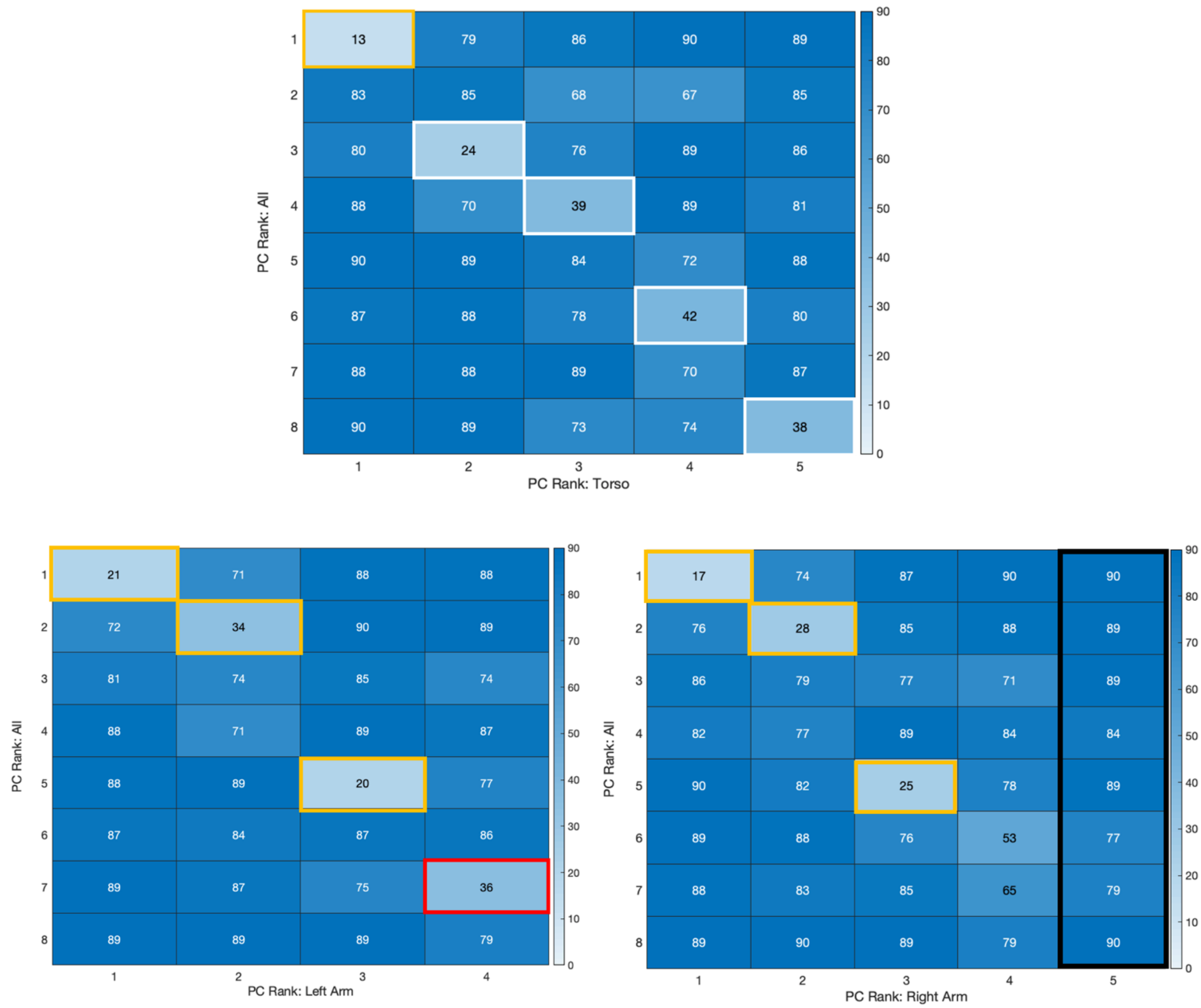


B) Left and Right Arm Comparisons



(figure continued on next page)

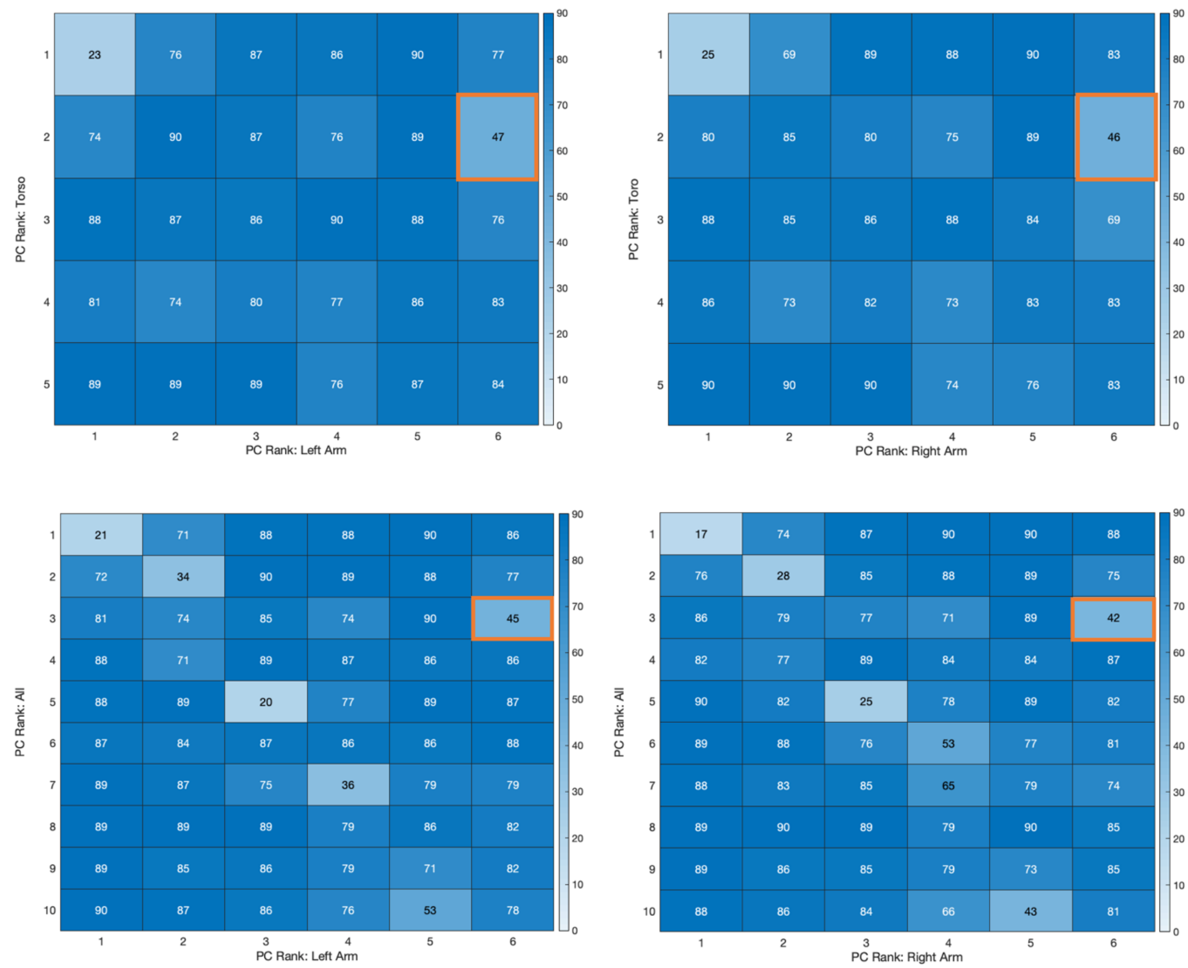
C) Torso-All and Arm-All Comparisons



Note. A) Solid black rectangles highlight where no subspaces can be identified. B/C) Yellow rectangles highlight subspaces common to all participants that represent task-determined variation. B/C) Red rectangles are left-specific subspaces in PCA^{all}. White rectangles are torso-specific subspaces in PCA^{all}.

Figure 7.42

Additional PC Subspace at 0.5% Variance Threshold, Blocked Octaves, Participant 1, Trial 1



It is interesting to note that the subspace characteristics of participant 1 showed clear evidence of independence between the right and left arms and between the torso and arms for both the blocked octave tasks and the contrary scales task. Future research could investigate whether these characteristics persist throughout other tasks in the battery for this participant, or if they are unique adaptations to these two tasks. Participant 1 has the most extensive background in somatic training, with many years of professional Feldenkrais training and personal practice. Part of this somatic approach involves learning to differentiate movement control in various parts of the body. Future research could investigate whether Feldenkrais training is associated with increasing independence of variation in functional groupings.

7.4.2.2.1 Summary of Results on PC Subspace Comparison in Blocked Octaves. The results from PC subspace comparisons in the blocked octave tasks demonstrates that functional subspace identification can effectively identify differences in coordination characteristics related to participant-specific strategies for coordinating the torso and the arms in a task requiring hand displacement in both the x- and -y axes. We were able to reveal the existence or absence of coordinative relationships between one or both arms and the torso by looking for subspaces between the torso and the arms. The degree of independence of those patterns within the larger data set can be determined based on whether arm-specific or torso-specific PCs are independently represented by PCs in PCA^{all}. Although this method can give an indication of the existence or absence of coordinative relationships related to the specific functional groups represented by the set of markers included in each PC, it is not possible to determine specific biomechanical sources of these coordinative relationships without developing further techniques or relating the subspace comparisons to inspection of raw motion capture trajectories. Furthermore, since most of the variation is described by the first two to three PCs in each subgroup, most participant-variation appears to be described by higher-numbered PCs. The identification of participant-specific subspaces will be improved by developing mathematical approaches for removing the task-determined variation patterns from the overall data set prior to running individual PCA on functional subgroups to target variation related to participants' musical and biomechanical choices.

7.5 Conclusion

Our work successfully identified evidence of one-dimensional PC subspaces in the motion capture data of pianists. Finding evidence of invariant PC subspaces in motion capture data is intriguing and important because it is not mathematically inevitable that they will occur in complex systems of variables. Our observation that PC subspaces are common when conducting functional subspace identification on subgroups of the motion capture data suggests that PCA is a useful tool for detecting the presence of coordinative structures in pianists' movement. We demonstrated that subspaces exist not only between PCA^{all} and $PCA^{subgroups}$, which point to the existence of persistent coordinative structures related to functional groupings of markers in the larger data set, but also between PCAs of completely independent subgroups, which do not share any common data. These second kind of subspaces are particularly powerful because they identify common variance patterns between separate sets of data. The existence of subspaces between independent functional groups suggest that the two data sets are coordinated in some way and can be used to gain insight into pianists' coordination strategies in different musical tasks. The results of this study suggests that subspaces between lower-numbered PCs (especially PC1) are most common and often have lower inter-PC angles indicating stronger similarities between the PCs in the pair. These subspaces tend to appear similarly in all participants for a given task and are therefore most related to task-determined variation. However, we were able to find several participant-specific examples of low inter-PC angles between higher numbered PCs, suggesting that unique subspaces can exist for individual pianists that may be strongly related to their personal coordination tendencies. Future research could test the persistence of these subspaces in individual pianists across task repetitions and across tasks in a larger group of participants. Future research could also examine how participants' unique subspace characteristics respond to movement retraining interventions, providing an objective way to track and measure the impact of movement retraining intervention on coordination characteristics.

The results of this study also demonstrated that the functional subspace identification can be used to identify participant-specific strategies for coordinating the arms and torso in tasks with different movement parameters. We found that identifying subspaces or the absence of subspaces between PCA^{right} and PCA^{left} could be used to determine whether pianists' arm movements were symmetrically coordinated for symmetrical task requirements, or whether each arm had unique variance characteristics. We were able to determine participant-specific strategies for coordinating the torso and the arms in the blocked octave task, which required pianists to repeatedly translate their hands horizontally through the x-axis for the entire length of the keyboard, while also translating forward and backward in the y-axis as they targeted alternating groups of three white and three black keys. Future research could apply functional subspace identification strategies to other tasks in the battery to examine whether participants exhibit consistent coordination strategies across different symmetrical or asymmetrical tasks, or whether the coordination characteristics are task-specific. Future research could also develop batteries of pianistic tasks to test specific hypotheses about the relationships between coordination characteristics and other variables. For instance, a study could be developed which explores whether pianists with histories of playing-related pain are more likely to exhibit asymmetrical coordination characteristics in symmetrical playing tasks compared to pianists with no histories of playing-related pain.

Finally, we found that comparing PC vectors using inter-PC angles was effective at highlighting evidence of coordinative relationships and invariant PC subspaces between subsets of motion capture data. Mapping inter-PC angles in PC subspace identification maps enabled quick identification of uniquely low angles providing an objective means of identifying potential subspaces without relying on time consuming, imprecise, and biased visual inspection of PC waveform characteristics. We found that the size of the angle itself was not as important as its size and uniqueness relative to other inter-PC angles involving PCs in the pair. For instance, we found that similarities between higher-numbered PCs were often indicated by uniquely small inter-PC angles in the range of 40-55 degrees for a given row or column in a PC subspace identification map, while similarities between lower numbered PCs were often indicated by inter-PC angles lower than 40 degrees. The size of the angle indicating a possible subspace depends on many factors, including the ranking numbers of the PCs in the pair, the characteristics of the task, and the presence of noise or overlapping patterns in higher-numbered PC waveforms. In future research it will be important to investigate how the magnitude of the inter-PC angles relate to the nature of the subspace relationships.

7.6 Discussion

Even though the functional subspace identification approach developed for this study identified instances of participant-specific subspaces related to individuals' unique coordination characteristics, their relative contribution to the overall variance in the data set was small when compared to the subspaces related to task-determined variation. The next step in our research will be to develop techniques for removing known variation related to task requirements prior to conducting functional subspace identification. We will explore using the musical pattern executed by the subject and encoded in the MIDI data of musical performances to create a task model matrix representing variation inherent in the task. By projecting the motion capture data onto the subspace represented by the task model matrix, the raw data can be transformed to include only variation perpendicular to the task model variation.

Removing variation related to the task may clarify subspaces related to coordination characteristics and enable identification of more specific relationships between subspaces and biomechanical features of the data. Although we hypothesize that removing the task determined variation will help to clarify participant-specific characteristics in the PCA, we must consider that the task requirements have an organizing effect on the whole data. We will not be able to fully predict what kind of coordinative relationships remain to be examined in functional subspace identification when the variation related to the required musical patterns is removed. It will also be important to remove biomechanical redundancy from the variation of the data by replacing the raw motion capture trajectories with a dimensionally reduced data set which can be done using standard PCA techniques. This will prevent common variation patterns shared between markers attached to the same rigid body from being entered multiple times into the PCA.

Taking steps to remove variation related to the musical pattern and to reduce biomechanical redundancy in the data could improve the ability of the functional subspace identification PCA approach to identify participant-specific coordination characteristics that could be tracked and measured over time to see if they are consistent for a performer, and if so, how the subspace characteristics respond when new movement patterns are taught via movement retraining interventions. Finding ways for PCA to target participant-specific variation could enhance the usefulness of functional subspace identification as a tool to investigate how other factors, such as playing-related pain, practice time, task complexity, or performance environment may impact pianists' coordination characteristics, paving the way for a more objective understanding of the factors that influence pianists' movements during performance.

It is important to highlight that the subspaces identified in this paper are one-dimensional only. The vector-to-vector inter-PC angles determine how close the vectors are to describing the same "direction" in the dimensional space of the data matrix. However, it is possible that subspaces exist in higher dimensions, such as between common two-dimensional planes, which could further clarify unique coordinative relationships between PCs. It is possible that even in the absence of a one-dimensional subspace, a two-dimensional subspace could exist. Future research will search for subspaces with dimension higher than one, but conducting the additional PC comparisons would require significantly more computational resources.

It is also important to consider that the results of functional subspace identification depend on how the researcher chooses to divide the markers into independent functional groups. For this study, we defined the functional groups based on a simple assumption that the arms and torso can move independently. This required the application of judgement as to which markers should be counted as arm markers, and which markers should be counted as torso markers. For instance, we decided that the acromion should be included in the arm groups since it is a part of the scapula, which moves with the rest of the arm. However, the acromion also shares movement variation characteristics with the torso, since the range of motion of the scapula is small and they can be held fixed depending on the habits of the performer. We decided to include the head as part of the torso for this study, but a case could be made for removing the head from the torso group, or including a head-only functional group, since the head is capable of rotating, flexing, extending, and side bending independently of the spine. Future approaches to functional subspace identification could experiment with adding or removing clusters of markers from different functional groups, or by creating more granular functional groups related to smaller independent subsystems, such as just the hand markers. It may also be possible to use clustering techniques to identify the most useful functional groups by identifying which subsets of markers share the most variation for a given performance. This might permit precision identification of subspaces related to specific joints or planes of motion within the larger functional group without visually inspecting raw motion trajectories for suspected sources of variation described by subspaces.

Finally, it should be emphasized that the concept of functional subspace identification as a means of enhancing the power of PCA to identify participant-specific coordination characteristics and track them over time could prove useful not only to researchers studying musicians' movement, but to researchers studying other complex human movement. Human kinetics researchers have always struggled to find strategies for identifying coordinative patterns underlying inherently variable data describing human movement. This challenge is made several orders of magnitude more difficult when many joint interactions are considered distributed throughout the body. The results of this paper demonstrate that functional subspace identification can help transform PCA from a tool best suited to making generalizations about human movement characteristics common to large groups into a tool that is capable of making more specific observations about the coordination characteristics of individuals. Further refinements are expected to increase its usefulness.

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CHAPTER 8: CONCLUSIONS AND DISCUSSION

8.1 General Conclusions

The purpose of this thesis was to address the need for an objective means of measuring pianists' coordination characteristics that is sensitive to subtle changes to movement relationships distributed throughout the body during complex movements, such as those required to play the piano. Such objective measures are required to support future research investigating the impact of The Feldenkrais Method on pianists' coordination characteristics because existing evidence from pilot research suggests that outcomes of the Method are most evident in how movement is organized throughout the body rather than in changes to the magnitude of individual joint angles or static postural characteristics. The thesis successfully addressed this topic by exploring the strengths and limitations of current PCA procedures for studying coordination characteristics and developing a framework for conceptualizing how different types of variation interact in motion capture data of pianists. The findings of this work were applied to develop a previously undescribed approach to conducting PCA analysis on motion capture data, *functional subspace identification.* By identifying persistent PC subspaces between independent PCAs conducted on functional subgroupings of the data, this method successfully identified coordination characteristics related to both musical task parameters and to pianists' unique movement choices. The initial application of functional subspace identification in this thesis suggests that this approach is promising, and that further refinement of the approach can be achieved by developing a procedure for removing pre-existing variation related to musical task patterns prior to conducting PCA.

The next few subsections review the conclusions of each of the five articles and provide discussions on their relevance in the greater context of research on complex movements and music and health research. This is followed by a summary of the main conclusions of the thesis, a discussion of the limitations of this study, and recommendations for future work.

8.1.1 Article 1-Conclusions and Discussion

The purpose of the article was to review existing research on somatic methods, including studies pertaining to musicians, to highlight the need for objective measurements of movement and body positioning in somatic research, rather than relying on qualitative reporting from practitioners and students. It provides a critical appraisal of various methods for measuring body positioning and posture that could be applied to research outcomes of somatic approaches, such as The Feldenkrais Method. A primary finding of this critical appraisal of measurement approaches is that it is difficult to find scientifically defensible definitions of good/healthy/effective characteristics of posture or body positioning that can be confidently applied in the context of piano playing. There are simply too many contrasting opinions and methods of measurement and to arrive at a clear definition of good, or healthy posture in piano playing based on existing research. As a result, the article concludes that it would be better for researchers to first look for evidence of changes to body positioning only, without attempting to define whether the changes should be considered improvements. Furthermore, the review concludes that contrary to what many teachers or somatic practitioners may believe, posture has not been strongly implicated as a factor in musicians' playing-related pain. The reasons for this are unclear. It may be that posture is an important factor but has been ineffectively measured in previous research. However, the review demonstrates that while much of the existing research on somatic methods has focused on measuring static posture or average body positions, little attention has been given to measuring movement and coordination characteristics in dynamic contexts. It may be that somatic methods influence how movements are coordinated more so than they influence structural alignment of different parts of the body.

This review article is primarily aimed at audiences in music pedagogy/performance, or musicians' health. Researchers studying somatic training outcomes for musicians likely have a background in music pedagogy/performance, or in somatic practices themselves. These fields come with their own preconceptions about the characteristics of good or healthy posture and movement, and many individuals seeking to study the influence of somatic methods on musicians' body positioning or movement likely already have a clear idea of what they believe improvements would look like. This is to be expected since these fields are pedagogic in nature and have their own theories and concepts to teach, many of which have histories decades, or in the case of some classical music techniques, centuries long. However, an important part of conducting objective research is to confront pre-existing beliefs and to test them for validity by studying available scientific literature. One of the main contributions of this article to the wider field of musicians' health is to give a survey of existing objective methods for measuring posture that could be used in somatic research and to point out their strengths and limitations so new researchers with backgrounds in music or somatic can make more informed decisions when constructing their methodologies. A second main contribution is to challenge the assumption that measuring static posture or average body positions is the best way of assessing somatic training outcomes objectively. Although this idea may already be evident to researchers with a background in biomechanics, researchers coming from an arts training background may be unaware of the strengths and limitations of different methods for assessing body position and movement quantitatively. This article introduces these ideas to researchers in musicians' health in an objective and non-confrontational way so that research in the field of somatics continues along a scientifically rigorous path.

8.1.2 Article 2-Conclusions and Discussion

The purpose of this article was to reflect on the results of a previous pilot study examining the impact of a single Feldenkrais FI lesson on fifteen advanced pianists' posture and movement (Beacon, 2015) to highlight the need for dynamic measurements rather than static measurements in Feldenkrais research. The results of the pilot study showed that average angles representing the position of the spine, shoulders, and head of pianists during the performance of musical tasks do not change significantly after a single FI lesson. However, article two highlights examples of motion trajectory plots from the pilot study that display striking changes to movement before and after the FI. Some individuals exhibited unique changes to the range of motion, frequency content of trajectories, and coordination of movement patterns between different markers on the spine and head. These changes in movement quality were not reflected in the average body position measurements. Reflecting on the results of the pilot study, article 2 makes five recommendations for conducting future research the impact of Feldenkrais lessons on pianists' movement (Beacon et al., 2021b):

1. Research on the Feldenkrais Method® with musicians may benefit from single-subject designs that use rigorous empirical methods to study changes in motor behaviour in individuals.

2. Research on how the Feldenkrais Method® influences movement quality and coordination may yield more poignant results compared to measuring static posture or averaging positions across an entire trial.
3. Future studies should include comprehensive baseline measurements to better understand the natural variability of the dependent posture and/or movement variables.
4. The posture and movement of a musician may be significantly influenced by the type of playing task they perform.
5. Researchers should acknowledge that it is difficult to interpret the meaning of posture measurements within the literature relating posture to health, function, or performance quality.

Article two provides data-derived evidence for one of the contentions made in article one; measuring changes to movement and coordination characteristics will yield more meaningful results in Feldenkrais research compared to average body positions. It also provides data-derived evidence that the types of movement changes observed will vary from person to person, making it difficult to choose specific kinematic variables *a priori* that would be suitable for assessing outcomes across all participants. Another contribution of this article musicians' health and human kinetics research is a survey of some possible methods for studying movement characteristics and body coordination that could be applied in future studies assessing the outcomes of somatic methods. The survey of methods for measuring coordination between many kinematic variables simultaneously highlights that although this kind of measurement is inherently more complex than measuring body positioning instantaneously, there are several possible methods that could be adapted with further testing. In particular, the article highlights PCA as a possible method for looking for movement relationships within complex motion capture data sets, setting up the PCA studies explored in articles three, four, and five.

8.1.3 Article 3-Conclusions and Discussion

The purpose of article three was to determine if standard PCA procedures as applied in previous studies on human movement are useful for detecting differences in coordination characteristics between four individual pianists performing pianistic tasks of varying levels of complexity. The results of the pilot study referenced in article two suggested that intervention research would benefit from further baseline testing to understand how coordination is expected to vary normally. Therefore, instead of conducting an intervention study, article three studies four participants three times, with the trials separated by one-week intervals. The results of the pilot study in article two also suggested that movement characteristics differ depending on task characteristics, such as whether the task is easy or more difficult, or whether the individual was sight reading or playing from memory. Therefore, the study in article three tested standard PCA on musical tasks with contrasting characteristics.

The results of article three showed that standard PCA output values, including: (1) the number of PCs required to describe 90% of the overall variance; (2) the percentage of overall variance described by the first three PCs; and (3) the number of PCs accounting for 2% or greater overall variance in the data set, are not on their own sufficient for distinguishing differences in coordination characteristics in pianists' performances based on (1) differences in musical task complexity; (2) differences arising from learning effects resulting from practicing the task; and (3) inter-individual differences between pianists. Just as the average posture measurement results were relatively uniform across pianists and tasks in the pilot study in article two, the PCA results in article three were quite uniform across different pianists, tasks, and trials. We determined that the standard PCA output values summarized variation characteristics related to piano playing in general, rather than pointing to unique coordination characteristics dependent on task parameters or participants' unique coordination choices. Examining PC waveforms and studying the MIDI data suggest that there were unique features in the movement and musical characteristics of different pianists' performances, but the standard PCA output values did not reflect differences where they might be expected based on the MIDI data and PC waveforms. Using standard PCA output values to distinguish coordination characteristics between pianists would likely only be useful when comparing two experimental groups with extremely large sample sizes, which is inconsistent with the goals of this thesis.

Interpretation of these results led to two important insights about the challenge of using PCA to identify unique coordination characteristics of pianists. First, the results of this study confirm that the movements involved in piano playing are substantially more complex than many of the other types of movement studied using PCA in previous research. We discovered that it generally takes about seven PCs to describe 90% of the overall variance for pianistic tasks, whereas many simpler movements can be summarized with two to four PCs. Secondly, the results prompted us to consider possibilities as to why the PC results were so uniform despite evidence in the MIDI and PC waveform data that suggested individuals had unique features in their playing. We hypothesized that the reason for the uniformity of the results may be related to the dominance of task-determined variation and anatomically determined constraints in the motion capture data sets. Variation related to the musical patterns would be consistent across participants for a given task, since the timing and location of notes would be pre-defined by the musical scores. Similarly, features of the movement variation would be consistent across all participants due to consistency in the anatomical structures and placement of the anatomical markers for all participants. We hypothesized that pre-determined variation related to task-constraints and anatomical structures common to all participants may dominate the variation in the data set and therefore be more strongly represented in the PCs accounting for the greatest proportions of the variance. Variation related to participant-specific musical or biomechanical choices may account for a much smaller percentage of the overall variance. PCA is not itself a measurement technique. Instead, it is a means of transforming a data set containing measurements to look at it from the perspective of relationships between variables. On its own, PCA cannot discriminate between variation that may be meaningful to answering a research question, such as subtle variation in coordination characteristics of pianists in response to movement retraining interventions, or variation related to pre-existing patterns, such as the patterns related to the musical tasks themselves. There are many different sources of variation contributing to the overall variation in motion capture data of pianists. Since PCA is a method of analysing patterns in variance, researchers must reflect on the possible sources of variation contributing to their data sets and consider which types of variation are most sensitive to experimental manipulations. Many studies using PCA do not consider the various sources of variation contributing to their data set. Future research applying PCA to human motion capture data of complex movements must develop frameworks that identify, categorise, and organize the different sources of variation layered into the motion capture data to aid in the interpretation of PC results and to help develop targeted PCA approaches that highlight variation related to participant-specific movement characteristics. This is particularly true of studies with musicians, where patterns related to the musical score are likely to contribute a significant proportion of the overall variation in the data set.

8.1.4 Article 4-Conclusions and Discussion

The purpose of this article was to respond to the need for a more comprehensive consideration of the different sources of variation submitted to PCA by developing a data-informed framework identifying and organizing different types of variation contributing to motion capture data of performing pianists. The first step in constructing a framework was comparing visual characteristics of PC waveforms to plots of pitch content from the MIDI data and raw movement trajectories from the motion capture data. The visual comparisons yielded five main conclusions:

1. The shapes of the PC waveforms contain information that can be used to link them to variation more strongly related to task-parameters or to participant choices.
2. Task-determined variation dominates the first and second PCs for the musical tasks investigated in this study, and therefore accounts for the greatest proportion of the overall variance in the data sets. This is evident due to the resemblance of one or more of the early PCs to pitch plots of the MIDI data. The PCs accounting for a greater degree of the variance tend to contain frequency content related to repetition of the entire musical task, repetition of the sub-tasks, and frequency of individual note presses.
3. Comparing the characteristics of PC waveforms from right and left arm separately for symmetrical pianistic tasks suggests that PCs ranked three or higher are more likely to

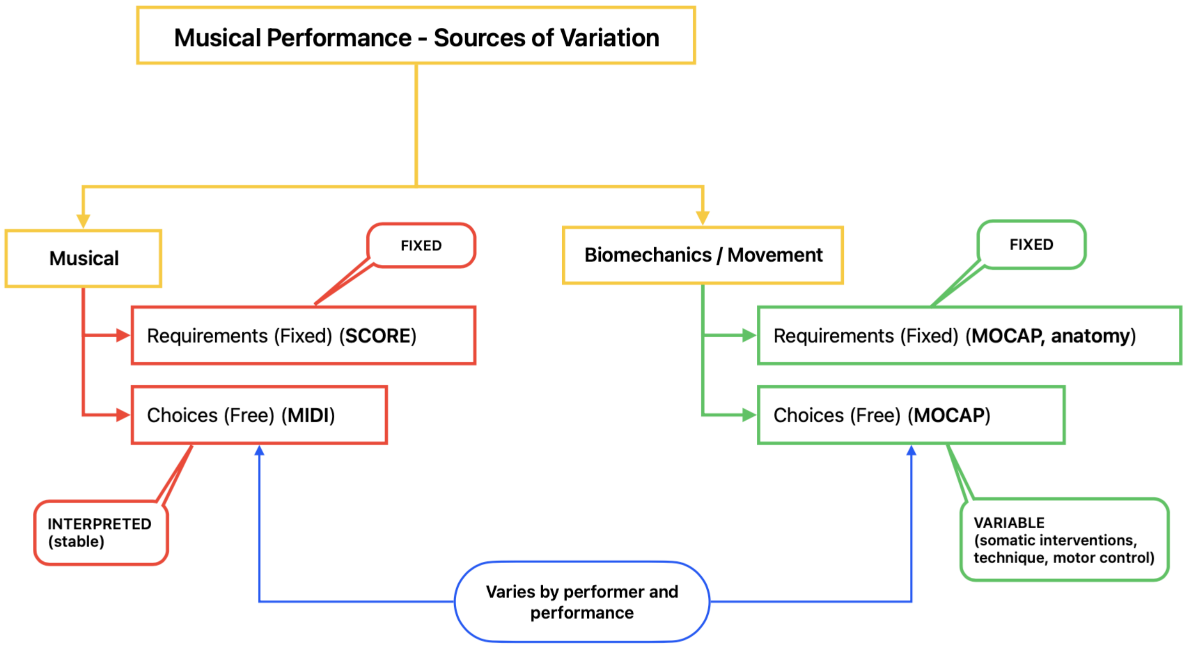
reflect participant-specific aspects of the variation in the data set. This is because arm PCs ranked three or higher (i.e., ranks 3, 4, 5 etc.) were more likely to be unique to the right or left arm, even though the arms were executing musically and biomechanically symmetrical tasks.

4. Evidence of frequencies related to task parameters can often be found even in smaller PCs that account for less of the variance. This suggests that task-dependent variance dominates the PCA and may be obscuring more subtle variation related to participants' musical or biomechanical choices.
5. Conducting separate PCAs on subgroups of the data based on anatomically functional groupings (torso, right arm, and left arm), can reveal examples PC waveforms common to a subgroup and to the global PCA including all the data. This suggests that there may be independent variation patterns occurring within subsets of motion capture data that persist even when data from the other groups is added to the PCA.

Reflecting on the variation characteristics observed in the comparisons of PC waveforms, raw motion trajectories, and MIDI plots enabled the identification and categorization of different kinds of variation present in the motion capture data of pianists. We recognized that motion capture data of pianists contains many sources of variation that can be categorized as primarily musical or biomechanical. Within each of these categories are aspects of the variation that remains fixed for all participants and aspects of the variation that can vary depending on the participants' individual choices. In the case of musical variation, variation related to patterns of timing and pitch dictated by the musical score of the task performed for a given test is a fixed source of variation that will be the same for all pianists performing the same task. However, some aspects of musical variation, such as micro-timing, dynamic inflection, sense of phrasing, overall tempo, and styles of articulation may differ depending on the pianist's musical interpretation of the task. In the case of biomechanical sources, variation related to the structural arrangement of joints and limbs in the human body and the placement of the anatomical markers will be common to all participants, since the same anatomical markers were used to represent the musculoskeletal structure of the human body for all participants, and all participants have the same available degrees of freedom afforded by the joints in the human body. However, individual pianists may choose to coordinate these degrees of freedom any number of ways to perform the task, and the part of the variation in the data set will relate to the performer's unique coordination characteristics. This is the source of variation we are most interested in detecting and measuring. These theories are arranged in the following visual representation of the framework for variation in music performance:

Figure 8.1

A Theoretical Framework of Variation in Music Performance



Although this specific framework was developed to help interpret different sources of variation in 3D motion capture data collected during the performance of fixed pianistic tasks, researchers using PCA to study other forms of complex movement using kinematic, kinetic, or even EMG data could develop similar frameworks to help organize their conceptualizations of the different sources of variation contributing to their data sets. One of the widest criticisms of PCA as an analysis tool for studying human movement is the lack of interpretability of the results. Since each PC contains information from every variable included in the PC and since the PCA cannot differentiate between different types of variation in the data set, researchers have struggled to physically interpret PCA results in terms of their relationship to identifiable physical phenomena or the behaviour of specific joints or limbs. Developing frameworks like the one presented in article four is an important first step for enhancing the interpretability of PCA results and for helping researchers develop PCA approaches that can target variation in the data set that is sensitive to experimental manipulations. Including these frameworks could become an important first step in research seeking to use PCA as a means of tracking change in a dependent variable in studies of human movement.

8.1.5 Article 5-Conclusions and Discussion

The purpose of article five was to develop a quantitative means of locating common PC waveforms between independent PCAs conducted on subgroups of the motion capture data. We originally observed evidence of common PC waveforms through visual inspection in article four. Article five explores our newly developed PCA procedure, *functional subspace identification,* for mathematically finding PC waveforms (PC subspaces) common to separate PCAs. Functional Subspace Identification involves conducting a global PCA on all motion capture data simultaneously, followed by separate PCAs on subgroups of the data divided chosen to reflect coordinative structures in the body that are capable of functioning independently. In our case, we conducted separate PCAs on the motion trajectories of the right arm, left arm, and torso. We compared the PC vectors by computing the inter-PC angle between the vectors. Smaller inter-PC angles indicated the PCs vectors represented similar variance in the data set and therefore could indicate the existence of a PC subspace common to two PCAs. Larger inter-PC angles meant the PC vectors represented dissimilar variance in the data set and were not related. Testing functional subspace identification on different musical tasks and comparing the results between six different pianists led to the following conclusions:

1. Functional subspace identification is an effective means of locating PC subspaces between separate PCAs on subgroups of the data.

2. Examples of PC subspaces can be found between different functional subgroups and between functional subgroups and the global PCA on all the data.
    a. PC subspaces between independent functional groups indicate that an aspect of the movement of the markers represented in the two groups is coordinated. In these cases, there is no common data between the PCAs, so discovering a common PC subspace is indicative of common variation patterns between two independent sets of data.
    b. PC subspaces between functional groups and the global PCA to the existence of independent coordinative structures within the full data set that remain consistent even when part of the data is removed. These subspaces can isolate variation characteristics within the full data set that can be mathematically linked to the variance of a subset of markers, such as those in the torso, right arm, or left arm.
3. PC subspaces can be used to identify task-specific coordination characteristics that are common to all participants.
    a. Common PC subspaces occur across PC1 and occasionally also along PC2 for PCA^{all}, PCA^{torso}, PCA^{left}, and PCA^{right} for all the musical tasks we investigated. These subspaces are usually consistent across participants for a given task and represent the greatest proportion of total variation in the data set.
    b. *Functional Subspace Identification* was able to identify expected features of symmetry and asymmetry in music with symmetrical and asymmetrical musical features.

4. PC subspaces unique to individual participants can be found, usually by comparing PCs ranked three or higher.
    a. Participant-specific subspaces may have unique waveform shapes which distinguish the pattern they represent from those found in other participants, similar to a movement fingerprint.
    b. The number and distribution of participant-specific PC subspaces can be physically interpreted to make mathematically defensible statements of an individual's coordination characteristics. For example, finding PC subspaces between the torso and the right arm, but not the torso and the left arm might suggest that the participant's right arm is coordinated with the torso for the task, but the left arm moves independently of the torso.
5. Inter-PC angles are an effective means of identifying PC subspaces, but the magnitude of the angle indicating a subspace varies depending on several factors, such as the rank of the PCs being compared. Higher ranked PCs tend to be more stochastic than lower ranked PCs. Therefore, the lowest inter-PC angles found between higher ranked PCs tend to be about 15 to 20 degrees higher than the lowest inter-PC angles found between lower ranked PCs.

The results of this study demonstrate that functional subspace identification is a promising tool for helping identify participant-specific coordination characteristics in pianists' motion capture data. Future research could be conducted to determine if the unique subspace characteristics of pianists discovered using functional subspace identification could be tracked over repeated measurements to offer a way of studying if pianists' coordination characteristics change in response to movement training interventions, such as the Feldenkrais Method.

Although we have applied it to motion capture data of pianists, functional subspace identification could be applied in the study of other types of complex human movement. Functional subspace identification makes a significant and novel contribution to the field of complex movement research by helping address the need to separate task-dependent from participant-specific variation raised in articles three and four. *Functional subspace identification* makes this possible by allowing researchers to search for common PCs across participants for a given task objectively. PCs common to all participants are likely to represent task-dependent variation. *Functional subspace identification* also helps enhance the physical interpretability of PC results, since it makes it possible to link PC-subspaces with the specific groups of markers included in the functional groups. The inability to physically interpret the meaning of PC output remains one of the primary criticisms of PCA as a means of studying complex human movement, and functional subspace identification uses an original strategy to address that issue.

8.1.6 Summary of Main Conclusions of Thesis

Articles one and two used a critical appraisal of existing literature and measurement methods to highlight strengths and limitations of current approaches for evaluating the impact of somatic methods on pianists' posture and movement. These assessments pointed to three main conclusions: 1) more objective measurements of body positioning and movement are required in somatic research with musicians; 2) the Feldenkrais Method appears to influence how movement is organized throughout the body in dynamic movement more than it impacts the average postural alignment of certain joints. Therefore, future research should use quantitative measures related to coordination and movement rather than posture; and 3) participating in the Feldenkrais Method may influence movement coordination differently for different pianists and depending on characteristics of the musical task they are playing.

Based on these recommendations from articles one and two, articles three, four, and five turned to the development of a PCA-based approach for measuring pianists' coordination characteristics that would be sensitive to coordinative relationships distributed throughout the pianists' bodies and that could be used to identify unique coordination characteristics specific to each participant. The results of these articles can be summarized by five main conclusions: 1) piano playing movements are more complex than many other types of movement previously studied using PCA; 2) standard PCA output values are not sensitive enough on their own to highlight pianist-specific or task-specific coordination characteristics in piano playing; 3) since PCA merely transforms the data set to give insight into its variation characteristics, researchers using PCA must clearly understand the different types of variation contributing to the data set and identify which aspects of the variation are free to vary in response to a manipulated variable and which aspects are fixed based on experimental controls. Both kinds of variation will be present in PCA results and developing a data-informed theoretical framework, like our *theoretical framework of variability in music performance*, can help researchers interpret the results of PCA and develop PCA approaches that target variation related to their research questions; 4) functional subspace identification is a novel and effective way for finding coordination characteristics related to task-dependent and participant-specific variation which could provide a means for tracking changes to pianists coordination in future research on the

Feldenkrais Method; and 5) most of the variation in the motion capture data sets of piano performance is dominated by task-determined variation. Future refinement of functional subspace identification will benefit from the addition of procedures for removing variation related to the musical pattern prior to conducting PCA.

8.2 Limitations

The primary limitation of the studies conducted in this thesis was the small number of participants. Recruiting during the Covid-19 pandemic proved extremely difficult. With only six participants completing three trials over three weeks, statistical comparisons between pianists or between trials were not possible. Due to this limitation, we did not conduct statistical comparisons of PC output values between participant or between trials for article one. At present, we have not yet developed a way to statistically compare PC subspace characteristics across participants or trials for article five. Future research would have to take steps to make the trial data statistically comparable across different participants and trials by normalizing the task repetitions and time dimension for the data sets. This will be explored in future research.

Even though the number of participants was small, the data collected from the six participants, each performing twelve musical tasks of varying level of difficulty with contrasting biomechanical and musical features resulted in a very rich motion capture data base that provided excellent grounds for testing novel PCA procedures. Since the pianists participating in the study had contrasting musical backgrounds, experience with pain, and different level of exposure to somatic training ensured that there were a variety of unique coordination features to look for in the data set. Taking the time to delve deeply into the data of six pianists was extremely fruitful and yielded insights into characteristics of the data and the nature of the PCA results that we would not have found had we studied a larger number of pianists more superficially. An in-depth study of a small number of participants turned out to be more appropriate for the current phase of research on this topic, which is still very new.

A second limitation of the study is that many of the findings in article four rely on visual comparisons of PC waveforms, which are subjective. However, the examples presented in article four were reviewed by two researchers for agreement. Furthermore, any visual similarities noted in articles four and five were cross referenced with the inter-PC angles once that approach was developed for article five to ensure that the visually identified subspaces were supported with mathematical evidence.

8.3 Recommendations for Future Work

The findings of this thesis have pointed to clear next steps in the research which will help refine the PCA procedures developed in this thesis so that they can be applied in future intervention studies on the Feldenkrais Method with musicians. The most urgent issue to solve in future research is to determine a procedure for removing variation related to the fixed musical pattern from the data prior to conducting PCA and functional subspace identification. Evidence from articles three, four, and five pointed to the dominance of variation related to musical task characteristics, which were strongly represented in the PCs accounting for most of the variance. Features of task-determined variation, such as frequency content related to the repetition of the task or individual key presses were frequently observed throughout all PCs for a given PCA, suggesting that variation related to individual coordination characteristics is being overshadowed by task-dependent variation. We have already devised a possible strategy for removing task-dependent variation from the data set which involves using the musical pattern encoded in the MIDI data of musical performances to create a task model matrix representing variation inherent in the task. By projecting the motion capture data onto the subspace represented by the task model, the raw data can be transformed to include only variation perpendicular to the variation in the task. We will test this approach in our forthcoming research. A related issue for future work is to find a procedure for reducing redundant variation in the data set by using a dimensionally reduced data set that combines similar variation represented by different motion capture trajectories. This will also be explored in our forthcoming research. These procedures would be done prior to conducting PCA and/or functional subspace identification to see how they influence the characteristics of individual PCs, or the PC subspace characteristics.

While the work presented in this thesis presents evidence of the utility of invariant PC subspaces for identifying participant-specific and task-specific characteristics in the variance of motion capture data that could be used to detect evidence of coordination change in pianists undergoing somatic training interventions, the techniques require further development and validation to permit their use in future studies. First, it would be helpful to validate our findings that the characteristics of PC subspaces related to different functional anatomical groups reflect expected coordination features by testing the approach using either a simulated data set representing pre-determined movement parameters or a data set in which pianists' movements were purposely constrained. For example, tests could be conducted on pianists playing with their torso movement physical constrained by a harness or brace to examine how that level of constraint impacts the independence of PC subspaces between the torso and the arms. Similarly, pianists could play with and without wrist braces unilaterally to study how that constraint impacts expected PC subspaces between the right and left arm. Such studies would validate the observations of PC subspace characteristics found in the present study, during which pianists' movements were partially constrained to certain planes by purposely selected task characteristics. Second, it will be necessary to conduct further testing to refine our understanding of how the magnitude of inter-PC angles relates to the degree of similarity between PCs and thus their utility in identifying subspaces. In the present study it was premature to seek to define the existence of a PC subspace with a specific magnitude of inter-PC angle, since the meaning of the magnitude of the PC angle is not well understood, especially for higher rank PCs. This will become clearer after future research on simulated or constrained data sets as well as after pre-processing steps for removing variation related to musical task requirements are established.

Future work on functional subspace identification should also look for PC subspaces in dimensions higher than one. In the present thesis, all PC subspaces were vectors, representing a "direction" in the dimensional space of the data matrix submitted to the PCA. Looking for PC subspaces in two dimensions could be thought of as looking for common planes between PCAs rather than common vectors. The number of computations and comparisons involved in generating all two-dimensional comparisons between two PCAs takes significantly more computational power and will be explored in future research.

The present thesis took a novel approach and examined the shape of PC waveforms to find meaning about pianists' coordination features. In other PCA studies, researchers are typically more concerned with studying the vector of weighting coefficients accompanying each PC that is simultaneously generated when conducting PCA. PC vectors can be multiplied by these weighting coefficients to reconstruct the original data. The weighting coefficients indicate how much of each variable is required in the reconstruction of the variance related to a given PC. Future research on functional subspace identification and PCA for identifying pianists' coordination characteristics could begin to include the weighting coefficients in the analysis to bring more precision to the physical interpretation of PCs. For instance, it is possible that examining the weighting coefficients of a PC subspace identified using functional subspace identification may reveal that coefficients related to some anatomical markers are very low, suggesting they do not contribute much information to that PC, while the weighting coefficients of other anatomical markers may be higher, showing that the variation represented by the PC is more directly related to those specific markers.

The battery of tasks developed for this research was vast and comprehensive. It included many technical and musical tasks of varying levels of complexity, and only a subset of full list was used in the development of this thesis. Future work could test the findings on a greater variety of musical tasks, including extending the functional subspace identification work to analyse more complex musical pieces, such as the *Valse Mignonne*, the Alberti Bass task. Developing pattern identification software for extracting individual musical layers from the more complex musical tasks was outside of the scope of this thesis but will be explored in future research.

Once the PCA and functional subspace identification procedures are refined based on the previous suggestions, they should be applied in future intervention studies on Feldenkrais with pianists. The first step should be to conduct an in-depth case study with extensive baseline testing and longer exposure to Feldenkrais Method. Data for such as study has already been collected and will be analysed in future research. Future intervention studies could compare the coordination characteristics identified using functional subspace identification with the visual assessments of trained somatic practitioners or other movement experts to see if they align. This would be a good first step toward being able to interpret whether potential coordination changes brought about by Feldenkrais could be considered improvements from the perspective of different fields of movement pedagogy. Future research could also investigate if certain coordination characteristics identified using PCA and functional subspace identification are correlated with pianists' level of expertise, history of playing-related pain or injury, or even experience of performing anxiety. It would also be very interesting to find out if certain coordination characteristics are associated with performance quality, as measured by piano performance juries.

PC Subspace Identification may also prove useful as means of assessing changes participant-specific coordination characteristics in other areas of human kinetics research. For instance, PC Subspace Identification could be useful in sports movement analysis for technique assessment. Researchers may be able to track changes to characteristics of PC subspaces in motion capture data to track changes in athlete's movements that might arise from new coaching or practice methods or to track changes in athlete's movements during rehabilitation and post-injury retraining. PC Subspace Identification might prove particularly useful for discrete sports tasks, such as a golf-swing, a volleyball serve, or a high jump, where subtle changes to motor coordination and timing have a direct impact on the successful execution of the task. PC Subspace identification may also be of value in assessing coordination characteristics in sports with an artistic component, such as figure skating, ballet, or rhythmic gymnastics, in which artistic variation is expected and encouraged despite the existence of defined technical execution parameters.

PC Subspace Identification may also be useful in rehabilitation research in applications where patients experiencing musculoskeletal injury, neurological injury, or motor control disorder might exhibit changes in movement coordination. For instance, PC Subspace Identification could be used to track disease progression by assessing changes to movement variability characteristics over time in disorders such as multiple sclerosis or Parkinson's Disease. It could be used to assess rehabilitation outcomes for individuals who have experienced stroke or individuals experiencing cerebral palsy. Such individuals may experience restricted degrees of freedom resulting from a loss of motor dexterity. Researchers may be able to track changes to PC subspaces as an indicator of increasing movement variability as rehabilitation leads to greater expression of the degrees of freedom in motor compromised individuals.

8.4 Concluding Remarks

The steps taken in the research presented in this thesis have laid the groundwork for developing meaningful PCA strategies that will provide an objective means of tracking changes to pianists' coordination characteristics for the purposes of evaluating the outcomes of Feldenkrais training. The work described here could be meaningfully applied to study other musicians, or complex human movement outside of the context of music. The step-by-step approach presented in this thesis, beginning with critical appraisals of current methodologies, moving through the development of necessary data-informed frameworks, and arriving at an innovative methodology highlights the importance of taking the time to deeply understand the subtle issues underlying the variables we are seeking to measure. The process of discovery that unfolded throughout the development of this thesis demonstrates that as with any measurement, the closer you get to measuring the variable being studied, the more elusive it can become as previously unknown factors become clear. This thesis successfully addressed the purpose of developing an objective means of measuring pianists' unique coordination characteristics. It will be exciting to further develop the methods introduced in the thesis and to test them on future intervention studies on Feldenkrais with pianists.

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APPENDIX A

ETHICS CERTIFICATES

Université d'Ottawa

Bureau d'éthique et d'intégrité de la recherche

University of Ottawa

Office of Research Ethics and Integrity

CERTIFICAT D'APPROBATION ÉTHIQUE I CERTIFICATE OF ETHICS APPROVAL

Numéro du dossier / Ethics File Number	H-03-19-3394
Titre du projet / Project Title	Investigating the impact of Feldenkrais Method lessons on the postural coordination patterns of pianists
Type de projet / Project Type	Thèse de doctorat / Doctoral thesis
Statut du projet / Project Status	Renouvelé / Renewed
Date d'approbation (jj/mm/aaaa) / Approval Date (dd/mm/yyyy)	06/08/2019
Date d'expiration (jj/mm/aaaa) / Expiry Date (dd/mm/yyyy)	05/08/2024

Équipe de recherche / Research Team

Chercheur / Researcher	Affiliation	Role
Jillian BEACON	École des sciences de l'activité physique / School of Human Kinetics	Chercheur Principal / Principal Investigator
Gilles COMEAU	Département de musique / Department of Music	Superviseur / Supervisor
Donald RUSSELL	Département de musique / Department of Music	Co-superviseur / Co-supervisor

Conditions spéciales ou commentaires / Special conditions or comments

550, rue Cumberland, pièce 154 550 Cumberland Street, Room 154
Ottawa (Ontario) K1N 6N5 Canada Ottawa, Ontario K1N 6N5 Canada

613-562-5387 • 613-562-5338 • ethique@uOttawa.ca / ethics@uOttawa.ca

Université d'Ottawa
Bureau d'éthique et d'intégrité de la recherche

University of Ottawa
Office of Research Ethics and Integrity

Le Comité d'éthique de la recherche (CÉR) de l'Université d'Ottawa, opérant conformément à l'*Énoncé de politique des Trois conseils* (2014) et toutes autres lois et tous règlements applicables, a examiné et approuvé la demande d'éthique du projet de recherche ci-nommé.

L'approbation est valide pour la durée indiquée plus haut et est sujette aux conditions énumérées dans la section intitulée "Conditions Spéciales ou Commentaires". Le formulaire « Renouvellement ou Fermeture de Projet » doit être complété quatre semaines avant la date d'échéance indiquée ci-haut afin de demander un renouvellement de cette approbation éthique ou afin de fermer le dossier.

Toutes modifications apportées au projet doivent être approuvées par le CÉR avant leur mise en place, sauf si le participant doit être retiré en raison d'un danger immédiat ou s'il s'agit d'un changement ayant trait à des éléments administratifs ou logistiques du projet. Les chercheurs doivent aviser le CÉR dans les plus brefs délais de tout changement pouvant augmenter le niveau de risque aux participants ou pouvant affecter considérablement le déroulement du projet, rapporter tout évènement imprévu ou indésirable et soumettre toute nouvelle information pouvant nuire à la conduite du projet ou à la sécurité des participants.

The University of Ottawa Research Ethics Board, which operates in accordance with the *Tri-Council Policy Statement* (2014) and other applicable laws and regulations, has examined and approved the ethics application for the above-named research project.

Ethics approval is valid for the period indicated above and is subject to the conditions listed in the section entitled "Special Conditions or Comments". The "Renewal/Project Closure" form must be completedfour weeks before the above-referenced expiry date to request a renewal of this ethics approval or closure of the file.

Any changes made to the project must be approved by the REB before being implemented, except when necessary to remove participants from immediate endangerment or when the modification(s) only pertain to administrative or logistical components of the project. Investigators must also promptly alert the REB of any changes that increase the risk to participant(s), any changes that considerably affect the conduct of the project, all unanticipated and harmful events that occur, and new information that may negatively affect the conduct of the project or the safety of the participant(s).

Coordonateur / COORDINATOR
Coordonnateur de l'éthique / Ethics Coordinator
Pour/For **Daniel LAGAREC** Président(e) du/ Chair of the **Comité d'éthique de la recherche en sciences de la santé et sciences / Health Sciences and Sciences Research Ethics Board**

Office of Research Ethics
4500 ARISE Building | 1125 Colonel By Drive
Ottawa, Ontario K1S 5B6
613-520-2600 Ext: 2517
ethics@carleton.ca

CERTIFICATION OF INSTITUTIONAL ETHICS CLEARANCE

The Carleton University Research Ethics Board-A (CUREB-A) at Carleton University has renewed ethics approval for the research project detailed below. CUREB-A is constituted and operates in compliance with the *Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans* (TCPS2).

Title: Investigating the impact of Feldenkrais Method lessons on the postural coordination patterns of pianists

Protocol #: 111364

Project Team Members: Jillian Beacon (Primary Investigator)
Donald L. Russell (Research Supervisor)
Dr. Gilles Comeau (Research Supervisor)

Department and Institution: Other External Organization, University of Ottawa

Funding Source (If applicable):

Effective: August 15, 2022 **Expires: August 31, 2023.**

Please ensure the study clearance number is prominently placed in all recruitment and consent materials: CUREB-A Clearance # 111364.

<u>Restrictions:</u>

This certification is subject to the following conditions:

1. Clearance is granted only for the research and purposes described in the application.
2. Any modification to the approved research must be submitted to CUREB-A via a Change to Protocol Form. All changes must be cleared prior to the continuance of the research.
3. An Annual Status Report for the renewal or closure of ethics clearance must be submitted and cleared by the renewal date listed above. Failure to submit the Annual Status Report will result in the closure of the file. If funding is associated, funds will be frozen.

4. During the course of the study, if you encounter an adverse event, material incidental finding, protocol deviation or other unanticipated problem, you must complete and submit a Report of Adverse Events and Unanticipated Problems Form.
5. It is the responsibility of the student to notify their supervisor of any adverse events, changes to their application, or requests to renew/close the protocol.
6. Failure to conduct the research in accordance with the principles of the *Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans 2nd edition* and the *Carleton University Policies and Procedures for the Ethical Conduct of Research* may result in the suspension or termination of the research project.

Upon reasonable request, it is the policy of CUREB, for cleared protocols, to release the name of the PI, the title of the project, and the date of clearance and any renewal(s).

Please email the Research Compliance Coordinators at ethics@carleton.ca if you have any questions.

CLEARED BY: **Date: August 15, 2022**

Natasha Artemeva, PhD, Chair, CUREB-B

Bernadette Campbell, PhD, Co-Chair, CUREB-B

APPENDIX B

COPYRIGHT PERMISSIONS

ARTICLE 1 AND ARTICLE 2

RE: Author requesting permissions to include two book chapters in doctoral dissertation

Claire Weatherhead [redacted]
Fri 2023-09-29 10:18 AM

To:Jillian Beacon [redacted]
Cc:Gilles Comeau [redacted] Russell Donald L.(Research Supervisor) [redacted]

Attention : courriel externe | external email

Hello

Thank you for your form.

We are happy to give gratis permission for the use of your chapters 6 and 7 (co-authored with Gilles Comeau, and Donald Russell) from 'The Feldenkrais Method in Creative Practice: Dance, Music and Theatre' edited by Robert Sholl in your Ph.D. dissertation 'Investigating PCA based techniques for objectively measuring the impact of the Feldenkrais Method on pianists' coordination characteristics' as outlined. Please ensure full credit is given to the original work, including editor, date of publication, title and Methuen Drama, an imprint of Bloomsbury Publishing Plc.

Kind regards

Claire

Claire Weatherhead
Permissions Manager
Bloomsbury Group Agency
Bloomsbury Publishing Plc

From: Jillian Beacon [redacted]
Sent: Thursday, September 28, 2023 9:13 PM
To: Claire Weatherhead [redacted]
Cc: Gilles Comeau [redacted]; Russell Donald L.(Research Supervisor) [redacted]
Subject: Author requesting permissions to include two book chapters in doctoral dissertation

[CAUTION: This email is from an external source. Exercise caution when opening attachments or clicking links]

Dear Ms. Weatherhead,

I am writing to request permissions to include copies of two book chapters I authored as articles in my doctoral dissertation at the University of Ottawa. The chapters are a part of a book entitled *The Feldenkrais Method in Creative Practice: Dance, Music and Theatre*, edited by Robert Sholl, published by Methuen Drama-Bloomsbury Publishing Plc. in 2021. The two chapters I am requesting permissions for are:

- Chapter 6-The Feldenkrais Method for Musicians: Addressing the Need for Objective

Measurements
- Chapter 7-Gaining Insight on the Impact of Feldenkrais Functional Integration in the Context of Piano Playing: Considerations for Measuring Posture and Movement Quality.

I am writing this request on behalf of myself and my two co-authors, Gilles Comeau and Donald Russell, who are also my thesis supervisors at the University of Ottawa. They included in CC on this email.

Please find the filled out Permissions Request Form attached to this email. Please let me know if you need anything else.

Sincerely,

Jillian Beacon
Ph.D. candidate, Human Kinetics
University of Ottawa

This email and its contents are confidential and may also be privileged and protected by copyright. If you are not the named recipient please notify the sender immediately, delete the email and all attachments completely from your system and do not use, print, copy, disclose or distribute any part of its contents. Bloomsbury Publishing Plc and its subsidiaries may monitor email traffic. Any views expressed in this email are those of the author, and do not necessarily represent those of Bloomsbury. This email does not conclude a binding agreement. Bloomsbury Publishing Plc 50 Bedford Square, London WC1B 3DP. Company registered in England and Wales company no. 1984336. Bloomsbury Publishing Inc. 1385 Broadway, Fifth floor, New York, 10018. Bloomsbury Publishing Pty Ltd, Level 4, 387 George St, Sydney, NSW 2000. Bloomsbury Publishing India Pvt. Ltd. DDA Complex, LSC , Building No.4, Second Floor, Pocket C-6&7, Vasant Kunj, New Delhi 110070. ABC-CLIO | Bloomsbury, ABC-CLIO is an imprint of Bloomsbury, 147 Castilian Drive, Santa Barbara, CA 93117.

APPENDIX C

PARTICIPANT CONSENT FORM

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Participant Consent Form (Pianists, Phase I)

Title of study: Investigating the impact of Feldenkrais Method lessons on the postural coordination patterns of pianists

Principal Investigator	Thesis Supervisor	Co-Supervisor
Jillian Beacon, Ph.D. Candidate, School of Human Kinetics University of Ottawa [redacted]	Dr. Gilles Comeau, Ph.D. School of Music, University of Ottawa [redacted]	Dr. Donald Russell, Ph.D. Associate Dean, Mechanical and Aerspace Engineering Carleton University [redacted]

Invitation to Participate: I am invited to participate in the abovementioned research study conducted by Jillian Beacon and supervised by Dr. Gilles Comeau. This is the Ph.D. thesis project of Jillian Beacon.

Purpose of the Study: The objective of the first phase of the study is to develop novel methods of analyzing motion capture data to better understand how Feldenkrais interventions impact coordination patterns of pianists. For this part of the study there is no Feldenkrais intervention. We are studying diverse pianistic movements to choose the best methods of analysis for a future case study on Feldenkrais for pianists.

Participation: As a participant in this project I will participate in the following data collection actitivies:

Three motion capture sessions:
I will participate in three motion capture sessions at the motion capture laboratory. The sessions are 50-60 minutes long and will take place on the same day of the week and at the same time of day for three consecutive weeks. At each session, I will perform eleven playing tasks. Nine of these tasks will be short musical exercises based on simple scale and chord patterns (30 seconds each). I will also perform a one-minute excerpt of a prescribed piece chosen from the Grade 8 RCM repertoire, and a one-minute excerpt of a piece of my own choosing. Performances of these playing tasks will be recorded with a video camera, and movements of my head, body, and arms will be tracked using a motion capture system. During motion tracking I will wear an tight-fitting

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athletic top provided to me by the researcher. Reflective adhesive markers will be placed on my wrists, elbows, and shoulders and hips, as well as four points on the spine. I will also wear a headband with reflective markers attached to it. I will fill out a demographic questionnaire at the first motion capture session.

I must practice the musical tests ahead of time so I can comfortably play them during testing. The music will be provided to me two-weeks before the first motion-capture session. The anticipated preparation time for practicing these pieces is 60 to 90 minutes. Each motion capture session lasts 50 to 60 minutes. Sessions will be scheduled at a time convenient for me in communication with the principal investigator. All motion capture sessions will take place in room A120 at Lees Campus the University of Ottawa.

*We ask that all participants and guardians arrive to the lab wearing a facemask. The university will also provide personal protective equipment, including facemasks and hand sanitizer. All research staff will be wearing facemasks and will cleanse their hands prior to interaction with the participants. All touched surfaces will be sanitized using a minimum 70% ethanol solution prior to and immediately after all data collection sessions. The motion capture room is very large and will permit a distance of two meters between the participant and the researcher at all times except for during the application of the motion tracking markers. During the application of anatomical markers the researcher will wear a lab coat, face mask, face shield, and gloves. The process of applying the markers lasts 5 to 8 minutes. We ask that particpants stay home if they are feeling ill. Please see the additional information appended to this consent form concerning Covid-19 risks and mitigation strategies.

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Data Collection Schedule of Activities

Moc-Cap Session 1 → Mo-Cap Session 2 → Mo-Cap Session 3

<one week> <one week>

- Each motion capture session lasts 50-60 minutes.
- Pianist performs nine technical tasks and two musical excerpts at each session.
- Data is collected at the same time and the same day of the week for three weeks.
- The participant may practice the musical tasks before the first session and between sessions if they wish.

Time/Location: All motion capture testing will take place in room A120 at Lees Campus, University of Ottawa:

Lees Campus, School of Rehabilitation Science
[redacted]

Appointments for motion capture sessions last 50-60 minutes and will be scheduled based on my availability.

Risks: Participation in this project involves live performance of music in front of researchers and a panel of three musical judges. As such, there is a risk that I may feel mild emotional or psychological discomfort due to shyness or performance anxiety. I may also feel mild physical discomfort due to repetitive motion of my fingers and wrists when performing musical tasks. I have received assurance from the researcher that every effort will be made to minimize these risks and that I will be offered many opportunities to rest and take breaks during data collection sessions. A debriefing session will also be offered to me at the conclusion of testing during which I may ask questions or raise any concerns I may have. I acknowledge that I am able to withdraw from

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participation of any research activity at any time for any reaons, including emotional or physical discomfort. Participation in this study or lackthereof will in no way impact participants' grades or academic standing.

Benefits: The study examines coordination patterns of pianists. Therefore, I may learn about features of my movement which may be of interest to me, such as gaining knowledge about aspects of my posture that may prevent me from playing more comfortably.The information I learn about my movement could help me in my studies/work as a pianist.

Compensation : I acknowledge that I will not be compensated for particpating in this research project.

Confidentiality and anonymity: I have received assurance from the researcher that the information I will share and the video and audio data of my performances will remain strictly confidential. I understand that all data will be used for analysis in this research study only and that my confidentiality will be protected. **Anonymity** will be protected in the following manner: My name will not be associated with any data, and I will be assigned a numeric code to be used by the researcher as a reference. Only the principle researcher, co-investigator, and authorized research assistants will have access to the master list of codes or pseudonyms that would link data to my identity. My identity will not be revealed in any publications.

Conservation of data: The video, audio, and demographic data collected on digital storage devices (such as SD cards, floppy discs, DVD's, and hard drives), and paper forms will be stored in a secure manner. All original data will be stored in locked filing cabinets in the Piano Pedagogy Research Laboratory, room 204, Pérez Hall, at the University of Ottawa. This lab is monitored by administrators during all office hours, is kept locked when unoccupied, and is equipped with an active alarm system at all times. Access to the data will be restricted to Jillian Beacon, Dr. Gilles Comeau, Dr. Donald Russell, and authorized research assistants who have signed a confidentiality form. The principal investigator, Jillian Beacon, will store the data indefinitely.

Voluntary Participation: I am under no obligation to participate and if I choose to participate, I can withdraw from the study at any time and/or refuse to answer any questions, without suffering any negative consequences. If I choose to withdraw, all data gathered until the time of withdrawal will be destroyed. Digital video and audio files will be deleted from digital storage devices, and demographic forms will be shredded.

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Acceptance: I, ____ agree to participate in the above research study conducted by Gilles Comeau and Jillian Beacon of the Department of Music, Faculty of Graduate Studies, at the University of Ottawa.

Consent for dissemination of images with me in them: I acknowledge that the researcher cannot guarantee my anonymity will be preserved if I consent to allow images or videos with me in them to be included in presentations, posters, or publications directly related to the dissemination of the results of this research study. The researcher has affirmed that the utmost care will be taken to safeguard my anonymity, even if I consent to have my images used in research publication material.

I consent to allowing the researcher to include images/videos with me in them in publications, posters, or presentations related to this research.

I <u>DO NOT</u> consent to allowing the researcher to include images/videos with me in them in publications, posters, or presentations related to this research.

If I have any questions about the study, I may ask the researcher at any point before, during, or after data collection.

If I have any questions regarding the ethical conduct of this study, I may contact the Protocol Officer for Ethics in Research, University of Ottawa, Tabaret Hall, 550 Cumberland Street, Room [redacted]

There are two copies of this consent form, one of which is mine to keep.

Participant's signature: Date:

________________________________ ________________________

Researcher's signature: Date:

________________________________ ________________________

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uOttawa Information Addendum - COVID-19 Risks

Principal Investigator: Jillian Beacon, Ph.D. Candidate, Human Kinetics

Study Title: Investigating the impact of Feldenkrais Method lessons on the postural coordination patterns of pianists

Please read the following statements carefully and feel free to ask questions if anything seems unclear.

We are putting in place safety precautions to reduce exposure to COVID-19, but the risk of exposure can still exist. COVID-19 can result in severe illness, medical expenses, and loss of income and in some cases, death.

If you are considered vulnerable to the effects of COVID-19 (e.g., an older adult; underlying medical conditions or a compromised immune system), please discuss your participation with the research team before consenting to participate.

If you are feeling unwell or experiencing any potential COVID-19 symptoms leading up to the research session, please stay home and notify the research team that you cannot attend. Should you experience symptoms in days following the session, please also notify the research team.

Potential COVID-19 symptoms include: new or worsening cough, shortness of breath or difficulty breathing, temperature equal to or over 38C (100.4F), feeling feverish, chills, fatigue or weakness, muscle or body aches, new loss of smell or taste, headache, gastrointestinal symptoms (abdominal pain, diarrhea, vomiting), or feeling very unwell.

To reduce the possibility of COVID-19, we have implemented the following safety procedures

- Regular handwashing
- Using hand sanitizer when handwashing is not possible
- Wearing of face masks/face coverings
- Physical distancing of a minimum of 2 meters (as recommended by the local health authority), except when applying anatomical markers*
- Limiting shared material and documents (pens, paper)
- Sanitizing surfaces and shared equipment prior to and immediately after each use
- Waiting 60 minutes between each session

- Using face shields or goggles when applying anatomical markers*
- Using lab coats when applying anatomical markers*
- Using gloves when applying anatomical markers*
- Collecting personal contact information for contact-tracing purposes.

Please advise a researcher if you believe a safety measure is not being taken, or that your safety is at risk.

Considerations for the Participant:

We ask that you:

- Wear a mask or face covering. Masks will be provided by the researcher if you do not have one. If you feel that you are unable to wear a mask, discuss your participation with the research team.
- Complete a screening assessment before each research session.
- Notify the researcher by text when you arrive at the research site so the researcher can safely direct you to the lab following signage for social distancing in the 200 Lees Campus building.
- Wash or sanitize your hands upon arrival. Hand sanitizer will be provided or a washing station will be available.
- Maintain physical distancing to the extent possible during the in-person research activities.

We ask that you follow the health-related directives above for your safety and the safety of the researchers.

Information for Contact Tracing

We are collecting personal contact information for contact-tracing purposes, in the event that you may have been exposed to COVID-19 at the research site. Your name and contact information:

- Will not be stored with the research data
- Will always be securely stored
- Will only be used if requested by Public Health authorities for COVID-19 contact tracing purposes
- Will be held only for the time required by Public Health authorities

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Right to Withdraw

You are under no obligation to participate. You can stop participating or withdraw from the study at any time by notifying the researcher using the contact information above.

Thank you for your interest and participation.

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Information for Contact Tracing (to be kept separately from research documents)

This information:

- will not be stored with the study data;
- will always be securely stored;
- will be used only if requested by public health to provide this information for COVID-19 contact tracing purposes; and
- will be held only for the time required by public health authorities

Name (please print): ____
(required)

Phone:
____(required)

Email:____(optional)

Name (please print): ____
(required)

Phone:
____(required)

Email:____(optional)

Date: ____