VALIDATION OF WEARABLE SENSOR PERFORMANCE AND PLACEMENT FOR THE EVALUATION OF SPINE MOVEMENT QUALITY

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Abstract

Inertial measurement units (IMUs) are being recognized as a portable and cost-effective alternative to motion analysis systems and have the potential to be introduced into clinical settings for the assessment of functional movement quality of the spine in patients with low back pain. However, uncertainties regarding sensor accuracy and reliability are limiting the widespread use and acceptance of IMU-based assessments into routine clinical practice. The objective of this work was to assess the performance of inexpensive wearable IMUs (Mbientlab MetaMotionR IMUs; Mbientlab Inc., San Francisco, USA; product specifications available in Appendix C) relative to conventional optical motion capture equipment (Vicon Motion Systems Ltd., Oxford, UK) in: 1) a controlled environment, and 2) an uncontrolled environment.

The first study evaluated the performance of 2 IMUs in a controlled environment during simulated repetitive spine motion carried out by means of a motorized gimbal. Root mean square error (RMSE) and mean absolute measurement differences between cycle-to-cycle minimum, maximum, and range of motion values, as well as correlational analyses within IMUs and between IMUs and Vicon, in all movement directions (i.e., simulated flexion-extension (FE), lateral bending (LB), and axial twisting (AT)), were compared. Measurement error was low in all axes during all tests (i.e., $\leq 1.54°$); however, low-to-moderate correlational results were found in one non-primary axis, and this axis changed depending on the direction of the movement (i.e., LB during FE-motion ($0.244 \leq R \leq 0.515$), AT during LB-motion ($0.594 \leq R \leq 0.795$), and FE during AT-motion ($0.002 \leq R \leq 0.255$)).

The second study was designed to assess the performance of the IMUs in an uncontrolled environment during repetitive spine FE in human participants. Absolute angles and local dynamic

stability were compared for individual IMUs (which were placed over T_{10}-T_{12} spinous processes, and the pelvis) as well as for relative motion between IMUs. Maximum finite-time Lyapunov exponents (λ_{max}) were used to quantify local dynamic stability and were calculated using both FE and the sum of squares (SS) from measured spine kinematics. It was found that the IMUs have acceptable performance in all axes when tracking motion (RMSE ≤ 2.43°); however, low-to-moderate correlational results were found in one non-primary axis ($0.987 \leq R_{FE} \leq 0.998$; $0.746 \leq$ RLB ≤ 0.978; $0.343 \leq R_{AT} \leq 0.679$). In addition, correlations between λ_{max} estimates were high; therefore, local dynamic stability can be accurately estimated using both FE and SS data ($0.807 \leq ICC_{2,1}^{FE} \leq 0.919$; $0.738 \leq ICC_{2,1}^{SS} \leq 0.868$). Correlation between λ_{max} estimates was higher when using FE data for individual sensors/rigid-body marker clusters; however, correlation was higher when using SS data for relative motion.

In general, the results of these studies show that the MetaMotionR IMUs have acceptable performance in all axes when considering absolute angle orientation and motion tracking, and measurement of local dynamic stability; however, there is low-to-moderate correlation in one non-primary axis, and that axis changes depending on the direction of motion. Future research will investigate how to optimize performance of the third axis for motion tracking; it will also focus on understanding the significance of the third axis performance when calculating specific outcome measures related to spine movement quality.

Co-Authorship

This thesis contains material from one published article (Chapter 4; adapted), and one article that will be submitted for publication (Chapter 5) once additional analyses are completed. The authorship is as follows:

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For each manuscript, K. Beange completed the tasks of: conceptualization and design of the research, acquisition of the data, analysis and interpretation of the data, writing the manuscripts, and critical revision of the manuscripts before submission and/or publication. Chapter 4 has been peer reviewed by IEEE committee members for the 2018 International Symposium on Medical Measurement and Applications (MeMeA) and is published online in the IEEE Interactive Electronic Library as part of IEEE Xplore; this version contains additional material that is not present in the published version (no results have been changed). An abstract for Chapter 5 was accepted for an oral presentation at the 2018 World Congress of Biomechanics in Dublin, Ireland; once additional analyses are completed, Chapter 5 will be submitted for publication.

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"I am thankful for my struggle, because without it I wouldn't have stumbled across my strength." – *Alex Elle*

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Definition of Terms

λ_{max}	Maximum finite-time Lyapunov exponent
1&2	Inertial measurement unit 1 versus inertial measurement unit 2
1&V	Inertial measurement unit 1 versus Vicon
2&V	Inertial measurement unit 2 versus Vicon
3D	3-dimensional
AOR	Axis of rotation
AT	Axial twisting
bpm	beats per minute
BLE	Bluetooth low energy
CAREN	Computer Assisted Rehabilitation Environment
cpm	cycles per minute
DST	Dynamical systems theory
FE	Flexion-extension
$ICC_{2,1}$	Intraclass correlation coefficient
IEEE	Institute of Electrical and Electronics Engineers
IMU	Inertial measurement unit
IMU_1	Inertial measurement unit 1
IMU_2	Inertial measurement unit 2
LB	Lateral bending
LBP	Low back pain
LDS	Local dynamic stability
LHCS	Left-handed coordinate system
MAMD	Mean absolute measurement difference
MAX	Maximum peak value
MIN	Minimum peak value
R	Pearson's correlation coefficient
RHCS	Right-handed coordinate system
RMSE	Root mean square error
ROM	Range of motion
SD	Standard deviation
SS	Sum of squares
wrt	with respect to

1.0 INTRODUCTION

1.1 Rationale for research

Low back pain (LBP) affects over 80% of people at some point in their lifetime (Andersson, 1999). Of these cases, 85-90% are classified as non-specific (Waddell, 2004), meaning that the pain cannot be attributed to any specific injury or pathology (Dillingham, 1995). In many cases (up to 70-80%), LBP can resolve within a period of a few weeks to months (Chou & Shekelle, 2010). However, a study by Donelson, McIntosh, and Hall (2012) revealed that over 60% of LBP sufferers reported chronic (i.e., lasting longer than 3 months) or recurrent symptoms (Donelson, McIntosh, & Hall, 2012) – both of which can be attributed to improper diagnosis and care, and are associated with poor prognosis (da Menezes Costa et al., 2012). LBP is the second leading cause of visits to a physician (Cox, 2012), and the leading contributor for years lived with a disability and missed work days around the globe (Hurwitz, Randhawa, Yu, Côté, & Haldeman, 2018; Kassebaum et al., 2016; Murray & Lopez, 2013). The cause of LBP is known to be multifactorial in nature, brought on by one or more pathoanatomical, neurological, physiological, psychological, and social contributors, making diagnosis and treatment of the disorder ambiguous and unreliable in the majority of cases (Waddell, 1987). Because of the extremely high prevalence and difficulty of diagnosis, LBP places a large socioeconomic burden on health care systems worldwide. More specifically, it accounts for up to $12 billion annually in Canadian health care costs (Back Care Canada, 2013), and $100 billion in the United States in total economic costs (Katz, 2006); that is, additional costs associated with loss of worker productivity, missed work days, disability payments, and related disorders that contribute further to the economic strain on society (Back Care Canada, 2013).

Despite the high prevalence of LBP, overall assessment and treatment of the disorder is substandard. The majority of current treatment strategies address pain and symptoms while overlooking the specific dysfunction underlying the low back disorder (O'Sullivan, 2005). There is a shift toward assessing spine movement quality and control to improve stratification of LBP diagnosis and care; however, visual appraisal is unreliable (Biely, Silfies, Smith, & Hicks, 2014; Fritz, Cleland, & Childs, 2007; Hicks, Fritz, Delitto, & Mishock, 2003; Stanton et al., 2011). Therefore, researchers and clinicians are shifting toward using wearables to provide objective assessments of movement quality.

The use of wearables for the assessment of movement quality is becoming increasingly popular in clinical and rehabilitation settings to improve patient subclassification for better guidance of treatment planning (Ashouri et al., 2017). More specifically, inertial measurement units (IMUs) are being recognized as a portable and cost-worthy alternative to conventional movement quality analysis technology (i.e., video-based optical motion capture equipment), and have the potential to be introduced into clinical settings for LBP assessment (Ashouri et al., 2017). Uncertainties regarding sensor accuracy and reliability, though, are limiting the widespread use and acceptance of IMU-based assessments into routine clinical practice (Bauer et al., 2015; Bolink et al., 2016; Cuesta-Vargas, Galán-Mercant, & Williams, 2010). Our lab group is developing a framework for performing wearable-based spine movement quality analyses in clinical settings using a custom mobile-based application and cloud computing (Graham & Josan, 2017; Ross, Beange, & Graham, 2018); however, prior to implementing the framework on a large scale, it is necessary to assess and validate the performance of the selected sensors for motion tracking and measurement of specific outcome measures associated with spine movement quality relative to gold-standard motion capture equipment; this is the primary goal of this thesis.

2.0 LITERATURE REVIEW

2.1 Low Back Pain

There is a lack of understanding concerning the underlying source of non-specific LBP as well as the appropriate treatment approaches to resolve it. Stratification of 'models of care' for LBP – that is based on personalized matching of patient subgroups to specific treatments – has been identified as an important future direction for LBP research and care (van der Windt, 2013). It is believed that the main reason for the difficulty of diagnosis is the fact that the LBP population is non-uniform, consisting of several smaller homogeneous subgroups (Bendebba, Torgerson, & Long, 2000; Kent & Keating, 2004; O'Sullivan, 2005). A new area of focus in LBP research is the subclassification of patient populations based on the identification of the mechanism underlying each disorder. O'Sullivan's (2005) biopsychosocial classification system is a well-accepted method of subclassifying LBP patients based on the presence and dominance of pathoanatomical, physical, neurological, physiological, psychological, and social factors that influence the disorder. Based on the identification and dominance of these biopsychosocial factors, it is possible to determine the causal pathways between pathological pain and movement control impairments, and determine whether the patient has adapted to the disorder in a negative manner (e.g., hypervigilance and fear avoidance behaviour, excessive stability, muscle guarding, and abnormal tissue loading; O'Sullivan, 2005). When patients develop inappropriate or maladaptive patterns of motion or methods of coping with their LBP (either subconsciously or physician-recommended), they put themselves at risk for developing recurrent or chronic LBP (O'Sullivan, 2005).

Within O'Sullivan's (2005) classification system, there exists a large group of patients (approximately 30% of those with non-specific LBP) who suffer from movement coordination impairment. This group of disorders typically presents in a directional manner and is associated with a lack of proprioceptive awareness of the lumbopelvic region, impairment or deficits in spinal stabilizing muscles, and subsequent loss of functional motor control of the neutral zone and movement of the spine. The onset is often gradual, and therefore these patients develop maladaptive postural and movement behaviour in response to pain that ultimately drives the chronicity of their low back disorder (O'Sullivan, 2005). As such, this group of disorders manifest in terms of altered movement quality, including excessive or poor stability, poor coordination of lumbopelvic segments, and a compensatory movement from thoracic and/or pelvic segments (Laird et al., 2016; O'Sullivan, 2005). Thus, correct objective identification of these movement behaviours is essential in providing appropriate intervention strategies to this large group of LBP patients.

2.2 Spine movement quality

While the root cause of LBP is difficult to diagnose, it is well accepted that spinal movement/motor control plays a large role in overall spine function and development of low back disorders (Nachemson, 1985; Panjabi, 1992a, 2003). Static and dynamic control of the spine depends on the interaction of 3 subsystems: 1) the passive subsystem (i.e., vertebrae, intervertebral discs, ligaments, and joint capsules), 2) the active subsystem (i.e., muscle forces), and 3) the control subsystem (i.e., neural elements; Figure 2.1; Panjabi, 1992; Reeves & Cholewicki, 2013; Reeves, Narendra, & Cholewicki, 2007). Disorders or deficits in any of these subsystems (e.g., poor proprioception, faulty control logic, longer neural delays, and degenerative changes to the osteoligamentous "passive" spine complex) can compromise an individuals' ability to control their spine, leading to the development of impaired and potentially harmful movement patterns (Reeves & Cholewicki, 2013; Reeves et al., 2007). Proprioception is an integral component that is required to achieve neural control of the spine, as it involves the sensations of position and movement of joints, feelings of force, effort, and heaviness associated with muscle contractions, and the sensations of perceived timing of muscular contractions (Gandevia, McCloskey, & Burke, 1992). LBP patients with movement coordination impairment experience altered movement behaviour, as it is believed that their disorder stems from a deficit in proprioception and functional motor control of stabilizing muscles within the spine (Burnett, Cornelius, Dankaerts, & O'Sullivan, 2004; O'Sullivan et al., 2003).

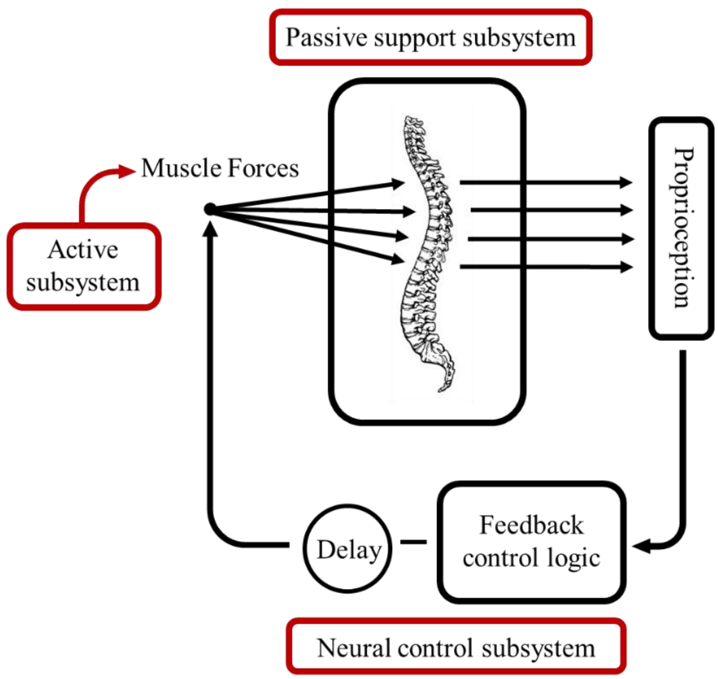


Figure 2.1. *Overall spine control system, consisting of active, passive, and neural control subsystems (adapted from Reeves et al., 2007).*

Professionals in both clinical and academic settings aim to assess spine movement quality and control to better understand the mechanisms underlying low back disorders; however, a disconnect exists between methods of assessment and evaluation of specific outcome measures in these domains. Clinical assessment of LBP typically involves visual appraisal of movement quality performed by primary and allied health professionals; however, it has been shown that both inter- and intra-rater reliability are low (Biely et al., 2014; Dankaerts, Sullivan, Straker, Burnett, & Skouen, 2006; Hicks et al., 2003; Spinelli, Wattananon, Silfies, Talaty, & Ebaugh, 2015). In addition, assessments in clinics typically involve supplementary self-report questionnaires, which introduces subjectivity into diagnosis. While these questionnaires provide useful information regarding treatment-outcomes from the patients' perspective that can help guide clinical decision making, it has been shown that objective and wearable-based evaluations are better at assessing movement quality features in experimental settings (Cook, Brismée, & Sizer, 2006; Dupeyron, Rispens, Demattei, & van Dieën, 2013; Howarth & Graham, 2015); however, it is not yet clear if it is clinically suitable. Currently, there is a lack of translation between the understanding of specific outcome measures in laboratory settings and their respective clinical application; therefore, there is a need for an objective means to be able to gather these specific outcome measures in clinical settings, and to provide clinically meaningful information to the healthcare provider regarding the patients' low back disorder.

2.2.1 Dynamical systems theory

The majority of studies that assess kinematic differences in people with LBP indicate that these patients possess aberrant patterns in trunk range of motion (ROM), angular velocity, and acceleration in all three movement planes at *discrete* points throughout a specific movement (Callaghan, Patla, & McGill, 1999; Van Lummel et al., 2013, 2016). However, measurement at discrete points limits analysis of inter-joint coordination, movement variability, and control mechanisms related to movement impairments (Silfies, Bhattacharya, Biely, Smith, & Gisztер, 2009) – measures that are important in understanding overall movement quality. It is well-accepted that patterns of motion and movement control of the spine develop through interaction and selforganization of active, passive, and neural feedback subsystems (Panjabi, 1992), and can be quantified using dynamical systems theory (DST) techniques. The DST approach to quantifying spine control and movement quality provides a comprehensive representation of the processes and subsystems utilized to achieve spinal control throughout the *entire duration* of a movement. It provides insight into individual patient movement and control profiles, as well as potential impairments, and is extensively studied in laboratory settings (Graham, Smallman, Miller, & Stevenson, 2015; Mokhtarinia, Sanjari, Chehrehrazi, Kahrizi, & Parnianpour, 2016; Silfies et al., 2009; Spinelli et al., 2015; Winstein & Garfinkel, 1989). Local dynamic stability (LDS) is a common feature used to quantify spine control and movement quality in LBP patients (M. Asgari et al., 2015; N. Asgari, Sanjari, & Esteki, 2017; Graham, Oikawa, & Ross, 2014; Graham et al., 2015; Ross, Mavor, Brown, & Graham, 2015), and has been documented to discriminate between people with acute and chronic LBP and healthy controls in experimental settings (M. Asgari et al., 2015; N. Asgari et al., 2017; Graham et al., 2014; Ross et al., 2015).

2.2.1.1 Local dynamic stability

Spinal stability is a sub-category that falls under the overarching idea of spinal control; it refers to the ability of the spine to return to a state of equilibrium when subject to both internal (i.e., intrinsic neuromuscular) and external (i.e., applied force or motion) disturbances (Reeves et al., 2007). Maintaining stability in *static* positions requires the spine to return to a desired stationary position or posture, whereas *dynamic* stability requires the spine to maintain equilibrium along a desired trajectory over time (Reeves et al., 2007). More specifically, LDS refers to dynamic stability in the presence of internal (i.e., “local”) perturbations that are inherent in the neuromuscular control system (Granata & England, 2006; Panjabi, 1992).

A common method of quantifying the LDS of the spine (i.e., the neuromuscular control of spine movement) involves implementing a nonlinear time-series analysis. The maximum finite-time Lyapunov exponent (λ_{max}) estimates LDS by quantifying a system's response to small internal perturbations during dynamic, repetitive tasks (Reeves et al., 2007; Rosenstein, Collins, & De Luca, 1993). It is used to describe local kinematic error, and its exponential growth or decay with respect to a reference trajectory (i.e., it measures kinematic divergence relative to *one's own* motion; Figure 2.2; Bruijn, Meijer, Beek, & van Dieën, 2010; Bruijn, van Dieën, Meijer, & Beek, 2009b; Graham & Brown, 2012; Graham, Costigan, Sadler, & Stevenson, 2011; Rosenstein et al., 1993). Researchers have found success in showing that trunk control and stability using λ_{max} can capture aspects of mechanical and clinical stability (Beaudette, Graham, & Brown, 2014; Graham & Brown, 2012, 2014; Mavor & Graham, 2015), can be collected using inexpensive wearable sensors (Graham, Sheppard, Almosnino, & Stevenson, 2012), and can quantify control changes associated with LBP (Graham et al., 2014) and clinical intervention (Southwell, Hills, McLean, & Graham, 2016). There is no "optimal" value for λ_{max}; rather, it is believed that a normal distribution curve can represent λ_{max} inter-subject variability within a given group of movers. To elaborate, the majority of healthy movers will fall somewhere in the middle of the distribution curve, and on both ends of the spectrum there are those who exhibit excessive stability or instability (i.e., "tight" and "loose" controllers, respectively; Figure 2.3; van Dieën, Reeves, Kawchuk, van Dillen, & Hodges, 2018). As such, assessing changes in motor control – quantified using λ_{max} – is a potentially useful method to classify differences in spine movement quality across the diverse spectrum of patients with LBP.

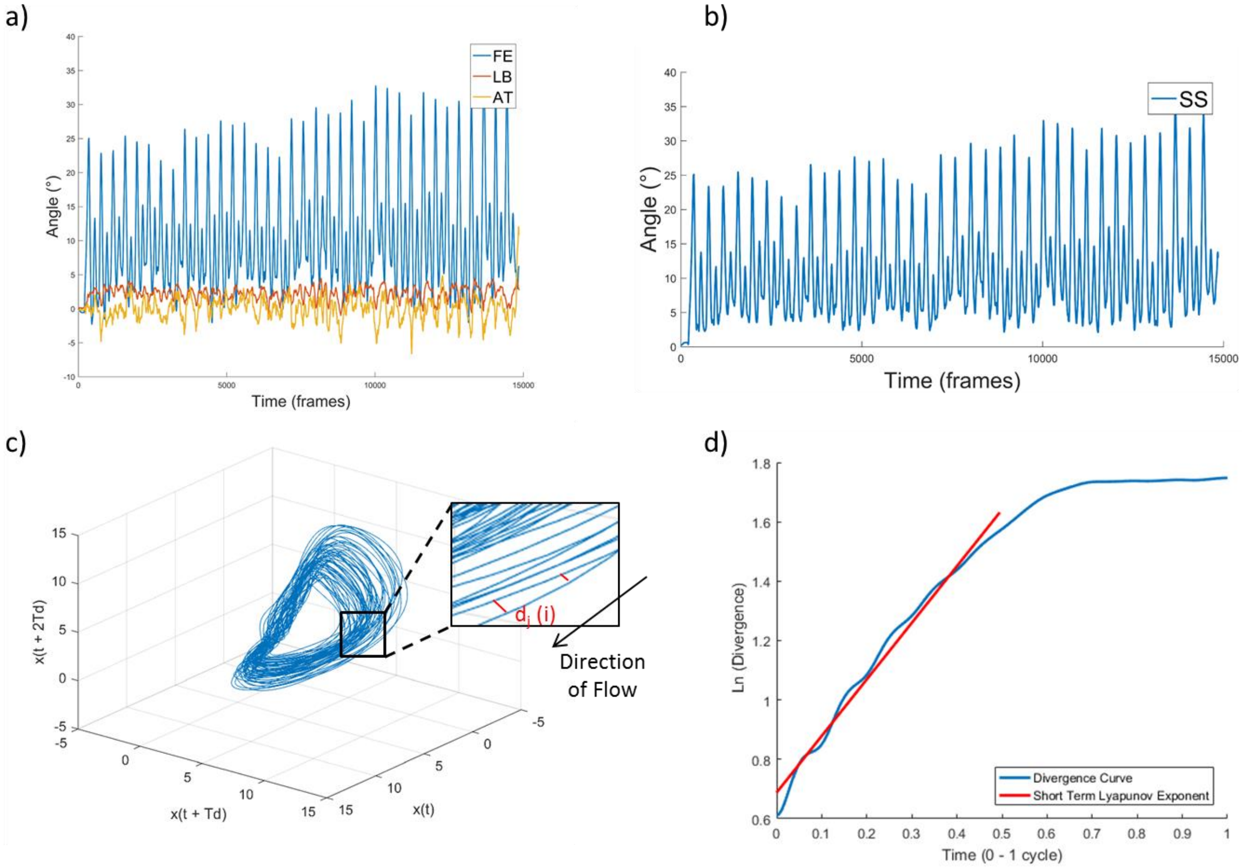


Figure 2.2. *Calculations of local dynamic stability (λ_{max}). (a) Original segment angles with respect to time (frames); FE = flexion-extension; LB = lateral bending; AT = axial twisting. (b) Sum of squares (SS) of the three Euler angles. (c) Dynamics in a multidimensional reconstructed state space with an expanded view of a local region on the attractor displaying divergence of nearest neighbours. (d) Average logarithmic rate of divergence for all nearest neighbor pairs over 0 – 0.5 cycles (λ_{max}; adapted from Mavor & Graham, 2015).*

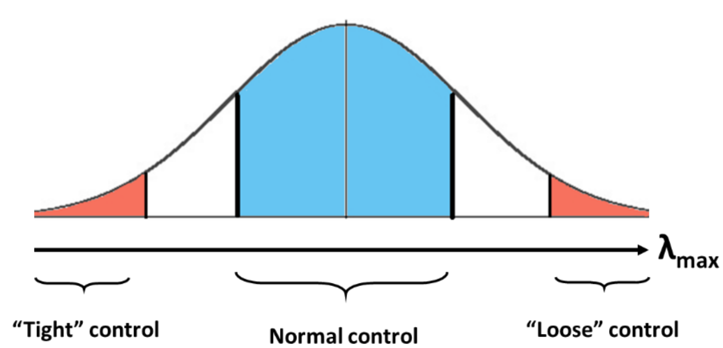


Figure 2.3. *Hypothetical normal distribution curve representing a majority of healthy movers with normal control, and those on either end of the LDS spectrum, who exhibit "tight" and "loose" control of spinal movements.*

2.3 Wearable sensors

The main issue with performing DST analyses for the purpose of LBP assessment is that it is difficult to accurately measure in clinical settings, as most of the equipment used is confined to a laboratory space (e.g., 3-dimensional (3D) video-based optical motion capture systems). Compounding this issue is the lack of knowledge transfer between clinical and academic professions regarding the clinical meaning of common specific outcome measures obtained in a laboratory setting, as well as the absence of an accessible platform that can provide clinicians with meaningful patient-specific movement profiles and appropriate treatments. While much of the research pertaining to assessment of spine movement quality is conducted in a controlled laboratory setting, there has been a shift toward using wearable IMUs and mobile-based applications paired with cloud computing for collection in applied settings (Mills, Morrison, Lloyd, & Barrett, 2007). IMUs are sensors that can record tri-axial linear accelerations (via an accelerometer), angular velocities (via a gyroscope), and sometimes magnetic distortion (via a magnetometer), and have been proven successful when estimating orientation and tracking motion in 3D global space (Bolink et al., 2016; Brodie, Walmsley, & Page, 2008; Madgwick, Harrison, & Vaidyanathan, 2011).

The increase in popularity of IMUs in clinics can be attributed to their ability to quickly and inexpensively collect, store, and analyze data outside of laboratory settings, providing real-time feedback via mobile-based applications (Patel et al., 2012). Commercial versions of such devices are already being used in a number of clinics across the globe, providing practitioners with immediate feedback on measures such as postural angle and ROM in 3 dimensions (viMOVE, © 2017 DorsaVi Ltd; Charry, Umer, & Taylor, 2011; Kent, Laird, & Haines, 2015). While some commercial IMUs have proven to aid in diagnosis and personalized feedback, more advanced analytical parameters (e.g., LDS) may improve the ability of physicians to understand overall spine movement and control, as well as the associated mechanism underlying each low back disorder, allowing for appropriate long-term treatment and management plans to be administered.

2.3.1 Sensor performance and validation

Despite the increasing popularity of IMU-based movement quality assessment, IMUs have not been accepted into routine clinical practice (Whelan, Reilly, Huang, Giggins, & Kechadi, 2016). This is likely due to both a lack of acceptance of sensor measurement accuracy in comparison to standard motion capture equipment, and a lack of acceptance and translation of IMU-based movement quality analyses into clinically meaningful diagnoses (Whelan et al., 2016). Compounding this issue is the lack of time physicians have to learn new technology, along with a general lack of technical savvy and/or confidence to effectively utilize new technology; thus, validation of IMUs for clinical motion tracking and evaluation of movement quality is required, along with a user-friendly platform that requires minimal training/technical experience. Existing literature pertaining to IMU performance assessment and validation relative to a gold-standard can be broadly categorized into two approaches: 1) assessment of IMU performance in a controlled environment (e.g., on a motorized gimbal); and 2) assessment in uncontrolled environments (e.g., on human participants; Ricci, Taffoni, & Formica, 2016). While the first approach highlights limitations inherent in the IMU by eliminating human factor sources of error, the second approach provides a more realistic validation scenario with respect to human-related applications (Ricci et al., 2016). As such, it is necessary to assess IMU accuracy and reliability in collecting clinically relevant data in both controlled and uncontrolled settings to provide a comprehensive assessment of overall performance.

Video-based optical systems are considered to be the laboratory gold-standard for human motion tracking, with an estimated accuracy error of less than 1°, and less than 1.5° root-mean-square error (RMSE) for static and dynamic measurements, respectively (Wong & Wong, 2008). The majority of these systems utilize passive-reflective markers that are tracked by multiple cameras and can be reconstructed via direct linear transformation algorithms to reproduce 3D motion of multiple body segments. While optical motion capture is regarded as highly accurate and reliable, setups are highly expensive and confined to a laboratory space, limiting accessibility for assessment in applied settings.

A recent meta-analysis by Cuesta-Vargas and colleagues determined that the degree to which an IMU system can be deemed valid is specific to the IMU system, post-processing algorithms, and anatomical site under investigation (Cuesta-Vargas et al., 2010). Researchers have tested the validity of various IMU systems relative to optical motion capture data for the assessment of spine motion in both primary and out-of-plane movement directions, and yielded absolute error ranging from 1.1° - 6.8° (Bauer et al., 2015; Goodvin, Park, Huang, & Sakaki, 2006). Under controlled conditions, Ricci et al. (2016) investigated the accuracy of IMUs in measuring typical human dynamics (i.e., repetitive sinusoidal motion), simulated by means of a robotic arm. In this study, it was determined that motion tracking accuracy is *slightly* dependent on the sensor fusion (i.e., post-processing) algorithms, *moderately* dependent on the amplitude and frequency of the movement itself, and *heavily* dependent on the orientation of the IMU, yielding errors of up to 10.3° (Ricci et al., 2016). Generally, an error of 2° or less is considered acceptable in clinical situations, and errors between 2° and 5° are regarded as reasonable, but may require additional interpretation (McGinley, Baker, Wolfe, & Morris, 2009).

Cuesta-Vargas et al. (2010) stress the importance of the post-processing algorithms in identifying and removing sources of error, which is something the majority of validation studies fail to emphasize. IMU's are susceptible to measurement drift and measurement noise, and therefore require filtering algorithms to correct for potential errors that may arise (Zhou & Hu, 2008). An orientation filtering algorithm is required to fuse separate sensor data (i.e., accelerometer, gyroscope, and magnetometer data) into a single estimate of orientation (most commonly Euler or Quaternion orientation). Euler angles are easily interpretable but have their drawbacks; because Euler orientation is defined by 3 variables, there are an infinite number of cases that represent the same orientation of the rigid body (Jung, Oh, Lim, & Kong, 2013), and thus gimbal lock can occur - a phenomenon in which 2 axes become locked (Lepetit & Fua, 2005; Mitchell & Rogers, 1965). These issues are avoided when using Quaternion orientation representation, as Quaternions are fully-defined by 4 variables; however, they are not as easily interpreted. Kalman filters are commonly accepted as a foundation for most orientation algorithms (Madgwick et al., 2011; Marins, Xiaoping Yun, Bachmann, McGhee, & Zyda, 2003). They filter out statistical noise, gyroscopic drift, influences from magnetic distortion, and other potential inaccuracies in measurements over time, by using probabilistic determination to predict what the system will do next (e.g., position and trajectory of body segments; Madgwick et al., 2011). The widespread use of Kalman-based solutions demonstrate their level of accuracy; however, the linear regression iterations utilized require high sampling rates that may exceed the sensor bandwidth, and demand a large computational load (Madgwick et al., 2011), which may not be ideal for real-time feedback using mobile-based applications.

Madgwick et al. (2011) generated a gradient descent algorithm that is applicable to IMU systems for orientation estimation and motion tracking. The proposed algorithms yielded lower

RMSE relative to a Kalman-based algorithm in measuring Euler angles yaw, pitch, and roll, and produced acceptable accuracy in comparison to optical motion capture technology. Additionally, the gradient descent algorithm achieved similar levels of performance at sampling rates of both 50 Hz and 512 Hz, proving that sampling rate can be minimized, which drastically reduces the computational load (Madgwick et al., 2011).

To obtain kinematics of the lumbar spine, sensors are usually placed on the pelvis and somewhere near the T_{12} spinous process (i.e., just above and below the lumbar region of the spine; Cholewicki & McGill, 1996). Commonly, thoracic and lumbar spine segments show high level of orientation measurement error in comparison to other body segments when directly comparing IMUs to gold-standard motion tracking equipment (Cuesta-Vargas et al., 2010). This is likely due to the natural anatomical curvature of the spine, such that relative spine angular kinematics are directly influenced by the number of vertebral segments that are spanned by the sensors (Howarth & Graham, 2015). As such, incorrect sensor placement could directly influence spine kinematic data. To highlight this, Harlick et al. (2007) asked physiotherapists to identify the location of specific spinous processes, and found that they were successful only 47% of the time, with an average error of 18.6 mm (roughly one spinal segment; Harlick, Milosavljevic, & Milburn, 2007). Moreover, Howarth and Graham (2015) evaluated the influence of electromagnetic sensor placement on measurements of peak angles and LDS of the lumbar spine and determined that positioning of the second sensor (i.e., the sensor relative to the pelvis sensor) at L_3 produced a 13% lower estimate of LDS than positioning the sensor at either L_1 or T_{11} (both of which showed strong agreement in LDS estimates). Instinctively, spanning more spinal motion segments also resulted in increased peak spine angle measurements (Howarth & Graham, 2015); therefore, error in sensor placement is quite substantial. Experimental setups using optical motion tracking cameras to measure spine kinematics affix rigid plate passive marker clusters to specified anatomical landmarks; however, these rigid plates typically span several vertebrae, introducing potential measurement error (Graham, Sadler, & Stevenson, 2011; Howarth & Graham, 2015; Howarth & Mastragostino, 2013). Additionally, rigid plate and/or IMU local coordinate systems are intended to line up with the local anatomical coordinate system (i.e., sagittal, transverse, and frontal planes) to accurately capture motion of the specified anatomical region. Therefore, misalignment of the rigid plate and/or IMU can introduce potential measurement error as a result of trigonometric calculation incongruity when estimating absolute orientation (Taylor, Miller, & Kaufman, 2017).

While many researchers have aimed to validate various IMU instruments and algorithms for spine orientation assessment, none, to the authors' knowledge, have evaluated the capability of IMU sensors and post-processing algorithms to measure advanced analytical parameters associated with LBP and spine movement disorders or associated neuromuscular deficiencies. Being that the validity of an IMU system depends on the specific instrument, post-processing algorithms, and the anatomical site being investigated, it is necessary to evaluate specific IMUs in both controlled conditions and in human participants (i.e., on the lumbar spine), and to assess the performance of the on-board post-processing algorithms in accurately tracking motion and measuring specific outcome measures associated with overall movement quality and control of the spine.

3.0 OBJECTIVE

The introduction of objective, wearable-based evaluation into clinical screening processes may reduce subjectivity and ambiguity of LBP diagnoses, providing clinicians with the ability to facilitate more appropriate treatment strategies to LBP subgroups. Prior to introduction into clinical assessments, the IMUs must be validated in their ability to accurately and reliably track motion, and to reproduce specific objective outcome measures that quantify movement quality of the spine. Therefore, the overall objective of this research is to validate the performance of wearable Mbientlab MetaMotionR IMUs for motion tracking and evaluation of spine movement quality. More specifically, the two main goals of this research are to:

1. evaluate the performance of the IMUs in a controlled environment (i.e., on a motorized gimbal) by assessing absolute error and correlation between repeated IMU measurements, and between IMU measurements and Vicon optical motion capture measurements during motion that is representative of typical human dynamics, and can be used to assess movement quality of the spine (i.e., repetitive sinusoidal motion) at varying frequencies (Chapter 4);
2. assess the performance of the IMUs in an uncontrolled environment (i.e., on the lumbar spine of human participants, during motion that permits the assessment of movement quality of the spine) by evaluating level of agreement, error, and correlation between IMU sensor measurements and Vicon motion capture measurements (Chapter 5).

4.0 ARTICLE 1: EVALUATION OF WEARABLE IMU PERFORMANCE FOR ORIENTATION ESTIMATION AND MOTION TRACKING

4.1 Abstract

Introducing objective wearable inertial measurement unit (IMU) assessments of functional movement quality into clinical practice may improve accuracy of diagnosis of movement-related impairments. The goal of the present study was to assess the performance of inexpensive wearable IMUs relative to conventional optical motion capture equipment in tracking motion during controlled movements that are representative of typical human movement. Thirty-five cycles of spine flexion-extension, lateral bending, and axial twisting were simulated by means of a motorized gimbal at speeds of 20 cycles/min (cpm) and 40 cpm, with an amplitude of 10°. Root-mean-square error (RMSE) and mean absolute measurement differences (MAMDs) between cycle-to-cycle minimum, maximum, and range of motion values, as well as correlational analyses within IMUs and between IMUs and Vicon, in all movement directions, were compared. All measurement differences and errors were low (i.e., MAMD $\leq$ 1.54°; RMSE $\leq$ 1.40°). There were very high correlations between repeated IMU measures ($R > 0.99$) in all movement directions showing reliability between IMUs and measurements. Overall, it was revealed that the sensors perform very well in the primary movement direction and one secondary axis; however, correlation in the third non-primary axis is suboptimal for orientation estimation and motion tracking. Future research will investigate how to optimize performance of the third axis for motion tracking during both controlled and uncontrolled tests.

4.2 Introduction

Clinical assessment of movement quality and impairment is used in a variety of domains across the healthcare spectrum. For example, it can be used to assess and subclassify LBP patients based on the level and type of their impairment (O'Sullivan, 2005), estimate risk of falling in older adults (Toebes, Hoozemans, Furrer, Dekker, & Van Dieën, 2012), and monitor physical and neurological rehabilitation status (Wattananon, 2014). Assessment of movement quality and impairment typically involves self-report questionnaires, visual assessment of movement patterns, and performance-based tests administered and scored by primary care providers and allied health professionals (Lebel, Boissy, Hamel, & Duval, 2013). This introduces subjectivity into diagnoses, and along with that, it has been shown that visual inspection of movement quality/impairment has poor inter- and intra-rater reliability (Spinelli et al., 2015). Introducing objective evaluation of movement quality and impairment into clinical assessments can improve the accuracy and reliability of certain diagnoses (Hemming, Sheeran, van Deursen, & Sparkes, 2018) in order to provide more effective and individualized care. Motion capture can be used as a tool to enable objective clinical evaluation.

Conventional motion capture systems are video-based optical systems requiring multiple cameras that triangulate the 3D position of retroreflective markers affixed to the participant. However, the cost and setup of these systems make them infeasible for routine clinical use. IMUs are becoming recognized as a portable and cost-effective alternative for motion capture, and have the potential to be introduced into clinical settings for objective assessment of functional movement quality (Ashouri et al., 2017). IMUs are sensors that can record tri-axial linear accelerations (via an accelerometer), angular velocities (via a gyroscope), and sometimes magnetic distortion (via a magnetometer), and have been proven successful in replicating both spatiotemporal (Moe-Nilssen & Helbostad, 2004) and kinematic data (Favre et al., 2006) in 3D global space by fusing individual sensor data to provide an estimation of absolute orientation.

In our laboratory we are developing a framework for performing wearable-based assessments of movement quality using inexpensive IMUs, a custom mobile-based application, and cloud computing. The Mbientlab MetaMotionR is a 9 degrees-of-freedom IMU incorporating an accelerometer, gyroscope, and magnetometer (Mbientlab Inc., San Francisco, USA). The MetaMotionR IMU was selected because it is cooperative with various programming languages and operating systems, it has on-board sensor fusion, and can be easily integrated into cloud-computing applications - all features that fit well into our framework. In addition, these IMUs were ideal because they can be purchased off the shelf and are inexpensive in comparison to other wearable systems (i.e., maximum $80USD/unit). In this work, we assess the performance of MetaMotionR IMUs through their ability to track orientation relative to conventional motion capture equipment.

4.3 Related Work

There is extensive IMU-related research investigating new sensor fusion algorithms for orientation estimation (Madgwick et al., 2011), the definition of protocols for practical usage with humans (Shull, Jirattigalachote, Hunt, Cutkosky, & Delp, 2014), and the extension to various clinical fields (e.g., assessment for orthopaedic, neurological, and rehabilitative professionals; Lebel et al., 2013). Despite the increasing popularity of IMU-based movement quality assessment, they have not yet been accepted into routine clinical practice (Whelan et al., 2016). This is likely due to a lack of acceptance of sensor measurement accuracy in comparison to conventional motion capture equipment. In addition, there is a lack of integration of clinically meaningful IMU-based assessments into routine clinical practice, as well as respective evidence-based rehabilitative success (Whelan et al., 2016).

Existing literature pertaining to IMU performance evaluation relative to a gold-standard for motion capture can be categorized broadly into two approaches: 1) assessing sensor performance in a controlled environment (e.g., on a motorized gimbal), and 2) assessment in an uncontrolled environment (i.e., on human participants; Ricci et al., 2016). While the first approach highlights limitations inherent in the IMU by eliminating human factor sources of error, the second approach provides a more realistic validation scenario with respect to human-related applications (Ricci et al., 2016). As such, it is useful to assess a sensor's accuracy and reliability in collecting clinically-relevant data in both controlled settings and in human populations; this study focuses on validation in a *controlled environment.*

Video-based optical motion capture systems are considered to be the laboratory gold-standard for human motion tracking, with an estimated accuracy (i.e., RMSE) of < 1.00° and < 1.50° for static and dynamic measurements, respectively (Wong & Wong, 2008). Generally, an error of 2° or less is considered acceptable in clinical situations. Errors between 2° and 5° are regarded as reasonable, but may require additional subjective interpretation (McGinley et al., 2009).

Ricci et al. (2016) investigated the accuracy of APDM Inc. Opal IMUs (APDM Inc., Portland, OR) in measuring typical human dynamics, simulated by means of a robotic arm. In this study, it was determined that motion tracking accuracy is *slightly* dependent on the sensor fusion algorithm, *moderately* dependent on the amplitude and frequency of the movement itself, and *heavily* dependent on the orientation of the IMU, yielding errors of up to 10.3° (Ricci et al., 2016).

Additionally, a meta-analysis completed by Cuesta-Vargas and colleagues (2010) determined that the degree to which an IMU system can be deemed valid is specific to the IMU system, fusion algorithms, and anatomical site under investigation. They stress the importance of the post-processing algorithms in identifying and removing sources of error, which is something that a large number of validation studies fail to emphasize or provide detail on (Cuesta-Vargas et al., 2010).

IMU's are susceptible to gyroscopic drift, inhomogeneous magnetic fields, and measurement noise – all of which have potential to introduce measurement error; therefore, IMUs require filtering algorithms to correct for error and improve measurement accuracy (Zhou & Hu, 2008). Kalman filters are commonly accepted as a foundation for orientation algorithms (Madgwick et al., 2011). They filter out statistical noise, gyroscopic drift, and other potential inaccuracies in measurements over time, by using probabilistic determination to predict what the system will do next (e.g., position and trajectory of body segments; Madgwick et al., 2011). The widespread use of Kalman-based solutions demonstrate their level of accuracy; however, the linear regression iterations utilized require high sampling rates that may exceed the sampling bandwidth, and demand large computational resources (Madgwick et al., 2011), which may not be ideal for real-time use with mobile applications.

4.4 Methods

4.4.1 Equipment and Experimental Setup

This study was designed to assess the accuracy and reliability of the MetaMotionR IMUs compared to a 7-camera passive optical motion capture system (Vicon MX40; 4 megapixels; Vicon Motion Systems Ltd., Oxford, UK) during controlled movement. Furthermore, this study involved the use of a Computer-Assisted Rehabilitation Environment (CAREN) Extended System

(Motekforce Link, Amsterdam, Netherlands) – a 6 degrees-of-freedom robotic joint allowing translation and rotation in all directions. This was used to facilitate controlled movements that are representative of typical human motion, to be tracked simultaneously by MetaMotionR IMUs and Vicon. Two IMUs were adhered to a rigid plate in the configuration shown in Figure 4.1, with 4 passive reflective markers in each of the 4 corners. The plate was firmly attached to the CAREN platform at the centre of rotation (Figure 4.2).

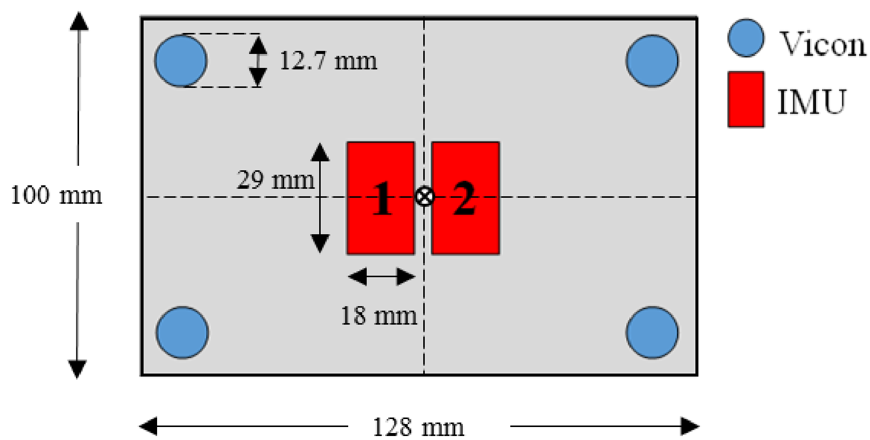


Figure 4.1. *Sensor setup and configuration; IMU_1 (left); IMU_2 (right).*

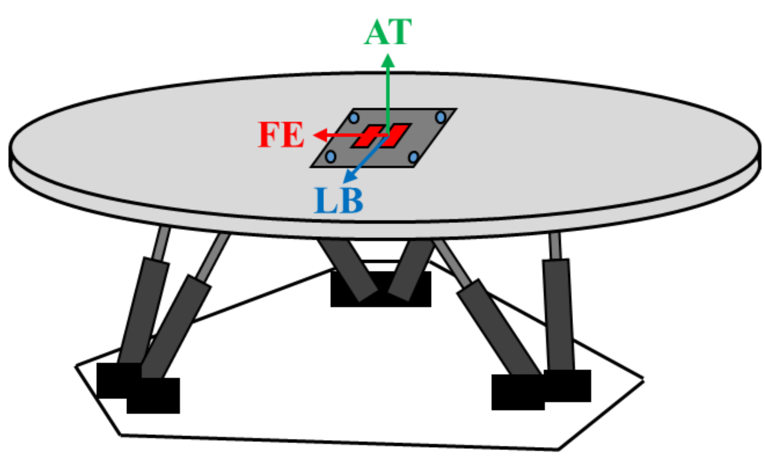


Figure 4.2. *Computer-Assisted Rehabilitation Environment (CAREN) system setup with the rigid plate/inertial measurement unit (IMU) placement.*

4.4.2 Movement Protocol

The movement protocol was designed to evaluate IMU performance at various speeds and in various movement directions. The CAREN software (D-Flow, Luleå, Sweden) was programmed to instruct the platform to simulate 3 idealized orthogonal movements: spine flexion-extension (FE), lateral bending (LB), and axial twisting (AT). Simulation of spine movement was chosen as it is extensively used to assess both physical and neurological impairments in a number of special populations (Mokhtarinia et al., 2016). In each trial, 35 cycles of a rotational sinusoidal movement was completed about the specified axis of rotation at 2 different frequencies: 1) 20 cpm, and 2) 40 cpm (M. Asgari et al., 2015; Granata & England, 2006). Amplitude of the sinusoid was programmed to ±15° from the axis-origin, about a single component axis (Barton, Vanrenterghem, Lees, & Lake, 2006). The center of the rigid plate was aligned with the axis-origin of the CAREN platform, and movement was conducted about this origin. A total of 6 trials (i.e., 2 speeds x 3 directions) were performed in randomized order. Data were sampled simultaneously from each IMU and from Vicon at 100 Hz. Absolute errors and correlations within IMU measurements, and between MetaMotionR IMU and Vicon measurements were evaluated.

4.4.3 Data Processing and Analysis

MetaMotionR IMUs are equipped with on-board sensor fusion and are capable of outputting continuous raw sensor data, Quaternion orientation, or Euler orientation. Sensor performance was evaluated using fused Euler orientation data to enhance interpretation. Data from Vicon and MetaMotionR IMUs were synchronized using the first peak maximum value in the primary movement direction for all tests. It is common practice to exclude the first 5 cycles of motion to ensure steady-state motion (Graham, Sadler, & Stevenson, 2012; Granata & England,

2006) when assessing human movement quality; therefore, to ensure consistency of analyses, the last 30 cycles were analyzed. Data from Vicon and MetaMotionR IMUs were low-pass filtered with a zero-phase Butterworth filter (effective 4th order with a cutoff frequency of 3 Hz) to filter out unwanted signal noise (Winter, 2010), and time-normalized by resampling the data for the 20 cpm trials and 40 cpm trials to 9000 samples per trial (i.e., 100 Hz x 30 cycles from peak-to-peak x 3 s/cycle), and 4500 samples per trial (i.e., 100 Hz x 30 cycles from peak-to-peak x 1.5 s/cycle), respectively. Gyroscopic drift was removed from the MetaMotionR IMUs by subtracting a least-squares line of best-fit from the data. A right-handed coordinate system (RHCS) was generated for the Vicon plate and Euler angles were extracted using a ZYX (i.e., AT-LB-FE) rotation sequence.

ROM was determined by taking the difference between cycle-to-cycle minimum (MIN) and maximum (MAX) Euler angles (i.e., FE (pitch), LB (roll), and AT (yaw); equations 4.1 – 4.3).

$$ROM_{FE} = \left| FE_{MAX}^{(pitch)} - FE_{MIN}^{(pitch)} \right| \tag{4.1}$$

$$ROM_{LB} = \left| LB_{MAX}^{(roll)} - LB_{MIN}^{(roll)} \right| \tag{4.2}$$

$$ROM_{AT} = \left| AT_{MAX}^{(yaw)} - AT_{MIN}^{(yaw)} \right| \tag{4.3}$$

4.4.4 Statistical Analysis

Differences in mean cycle-to-cycle ROM, MIN, and MAX values, as well as Pearson's correlations (R) and RMSE (°) for continuous data were compared between IMU_1 and Vicon, between IMU_2 and Vicon, and between IMU_1 and IMU_2 in all movement directions. Any R-values above 0.7 can be regarded as a strong positive correlation, with 1.0 being perfect correlation (Cohen, 1988). Values between 0.3 and 0.7 represent weak to moderate positive correlation. These trends are the same for negative correlations, but are represented as negative values (Cohen, 1988).

4.5 Results

The IMUs showed excellent agreement between mean absolute cycle-to-cycle MIN, MAX and ROM estimate differences in the primary axis of rotation, yielding a maximum mean absolute measurement difference (MAMD) of 1.54° between IMU_1 and Vicon, and a maximum RMSE of 1.40° between IMU_2 and Vicon, both during the 20 cpm FE task (Table 4.1; Table 4.5). Similar trends were shown between both IMUs 1 and 2 and Vicon. Differences between estimates of MAX, MIN, and ROM in the other two axes were also low, yielding a maximum MAMD of 1.20° during the 40cpm test when measuring ROM in the AT plane, during FE-based motion (Table 4.3).

The maximum MAMD in orientation between IMU_1 and IMU_2 was 0.50° when measuring MIN FE orientation during an AT test. Correlations between continuous Vicon and IMU primary axis data were very strong (Figure 4.3.; Figure 4.4.; results for IMU_1 are shown – results for IMU_2 showed similar trends). Correlations between IMU_1 and IMU_2 continuous data in the primary axis of rotation during all tests were greater than 0.99, as shown in Table 4.4 and Figure 4.5.

Table 4.1. *Mean absolute measurement difference (MAMD) from cycle-to-cycle minimum (MIN) measurements.*

Speed	***AOR***	***Measure***	***FE (°)***			***LB (°)***			***AT (°)***		
			1&V	***2&V***	***1&2***	***1&V***	***2&V***	***1&2***	***1&V***	***2&V***	***1&2***
20 cpm	**FE**	**Mean**	1.54	1.4	0.14	0.41	0.41	0.06	0.11	0.3	0.41
		SD	0.12	0.11	0.03	0.06	0.02	0.03	0.08	0.03	0.08
	LB	**Mean**	0.81	0.94	0.13	0.43	0.39	0.12	0.12	0.14	0.2
		SD	0.02	0.03	0.02	0.13	0.04	0.06	0.08	0.08	0.06
	AT	**Mean**	0.09	0.18	0.25	0.19	0.12	0.07	0.11	0.24	0.13
		SD	0.05	0.07	0.07	0.09	0.06	0.04	0.08	0.08	0.09
40 cpm	**FE**	**Mean**	1.24	0.93	0.31	0.46	0.32	0.14	1.09	0.59	0.5
		SD	0.41	0.56	0.18	0.03	0.08	0.09	0.06	0.05	0.07
	LB	**Mean**	0.17	0.29	0.12	0.84	0.81	0.04	0.37	0.36	0.22
		SD	0.22	0.21	0.06	0.03	0.05	0.02	0.22	0.14	0.14
	AT	**Mean**	0.15	0.1	0.08	0.24	0.18	0.08	0.17	0.17	0.03
		SD	0.07	0.07	0.04	0.13	0.05	0.05	0.12	0.11	0.02

*** grey shading indicates results from the primary movement direction. AOR = axis of rotation, FE = flexion-extension, LB = lateral bending, AT = axial twisting, 1 & V = IMU_1 vs. Vicon, 2 & V = IMU_2 vs. Vicon, 1 & 2 = IMU_1 vs. IMU_2, cpm = cycles/min, SD = standard deviation.*

Table 4.2. *Mean absolute measurement difference (MAMD) from cycle-to-cycle maximum (MAX) measurements.*

Speed	***AOR***	***Measure***	***FE (°)***			***LB (°)***			***AT (°)***		
			1&V	***2&V***	***1&2***	***1&V***	***2&V***	***1&2***	***1&V***	***2&V***	***1&2***
20 cpm	**FE**	**Mean**	0.80	0.88	0.07	0.14	0.10	0.07	0.10	0.09	0.19
		SD	0.13	0.14	0.03	0.05	0.01	0.03	0.07	0.03	0.08
	LB	**Mean**	0.92	0.57	0.35	0.17	0.30	0.16	0.16	0.10	0.18
		SD	0.02	0.03	0.02	0.13	0.04	0.10	0.10	0.07	0.06
	AT	**Mean**	0.19	0.32	0.14	0.08	0.08	0.09	0.10	0.08	0.10
		SD	0.07	0.08	0.08	0.04	0.04	0.04	0.06	0.06	0.07
40 cpm	**FE**	**Mean**	0.32	0.51	0.19	0.16	0.14	0.11	0.11	0.09	0.20
		SD	0.42	0.42	0.08	0.05	0.07	0.06	0.07	0.05	0.06
	LB	**Mean**	0.16	0.37	0.38	0.11	0.11	0.02	0.35	0.14	0.26
		SD	0.16	0.13	0.06	0.03	0.03	0.02	0.15	0.11	0.20
	AT	**Mean**	0.32	0.36	0.04	0.11	0.06	0.09	0.16	0.09	0.08
		SD	0.08	0.11	0.04	0.06	0.04	0.08	0.08	0.05	0.03

** grey shading indicates results from the primary movement direction. AOR = axis of rotation, FE = flexion-extension, LB = lateral bending, AT = axial twisting, 1 & V = IMU_1 vs. Vicon, 2 & V = IMU_2 vs. Vicon, 1 & 2 = IMU_1 vs. IMU_2, cpm = cycles/min, SD = standard deviation.

Table 4.3. *Mean absolute measurement difference (MAMD) from cycle-to-cycle range of motion (ROM) measurements.*

Speed	***AOR***	***Measure***	***FE (°)***			***LB (°)***			***AT (°)***		
			1&V	***2&V***	***1&2***	***1&V***	***2&V***	***1&2***	***1&V***	***2&V***	***1&2***
20 cpm	**FE**	**Mean**	0.73	0.52	0.21	0.33	0.29	0.04	0.21	0.39	0.59
		SD	0.03	0.05	0.04	0.01	0.01	0.02	0.02	0.01	0.02
	LB	**Mean**	0.11	0.37	0.47	0.39	0.49	0.09	0.17	0.21	0.37
		SD	0.02	0.02	0.01	0.02	0.01	0.02	0.04	0.04	0.04
	AT	**Mean**	0.11	0.49	0.38	0.20	0.05	0.15	0.21	0.29	0.07
		SD	0.03	0.04	0.05	0.01	0.01	0.01	0.03	0.04	0.06
40 cpm	**FE**	**Mean**	1.11	0.90	0.20	0.31	0.14	0.16	1.20	0.50	0.70
		SD	0.10	0.10	0.02	0.03	0.03	0.03	0.04	0.05	0.02
	LB	**Mean**	0.12	0.62	0.49	0.23	0.19	0.03	0.14	0.46	0.32
		SD	0.03	0.03	0.01	0.05	0.05	0.01	0.10	0.08	0.05
	AT	**Mean**	0.22	0.30	0.07	0.27	0.13	0.14	0.32	0.24	0.07
		SD	0.07	0.05	0.04	0.03	0.03	0.01	0.07	0.06	0.02

*** grey shading indicates results from the primary movement direction. AOR = axis of rotation, FE = flexion-extension, LB = lateral bending, AT = axial twisting, 1 & V = IMU_1 vs. Vicon, 2 & V = IMU_2 vs. Vicon, 1 & 2 = IMU_1 vs. IMU_2, cpm = cycles/min, SD = standard deviation.*

Table 4.4. *Results for Pearsons correlation coefficient (R).*

Speed	***AOR***	***FE***			***LB***			***AT***		
		1&V	***2&V***	***1&2***	***1&V***	***2&V***	***1&2***	***1&V***	***2&V***	***1&2***
20 cpm	**FE**	0.996	0.994	0.999	0.244	0.2777	0.969	0.934	0.947	0.944
	LB	0.983	0.949	0.940	0.999	0.999	0.999	0.594	0.764	0.795
	AT	0.002	0.027	0.827	0.846	0.840	0.851	0.999	0.999	0.999
40 cpm	**FE**	0.997	0.995	0.999	0.515	0.961	0.515	0.545	0.462	0.808
	LB	0.823	0.673	0.919	0.999	0.999	0.999	0.881	0.903	0.993
	AT	0.255	0.220	0.973	0.809	0.839	0.989	0.999	1.000	0.999

*** grey shading indicates results from the primary movement direction. AOR = axis of rotation, FE = flexion-extension, LB = lateral bending, AT = axial twisting, 1 & V = IMU_1 vs. Vicon, 2 & V = IMU_2 vs. Vicon, 1 & 2 = IMU_1 vs. IMU_2, cpm = cycles/min.*

Table 4.5. *Results for root mean square error (RMSE), (°).*

Speed	***AOR***	***FE***			***LB***			***AT***		
		1&V	***2&V***	***1&2***	***1&V***	***2&V***	***1&2***	***1&V***	***2&V***	***1&2***
20cpm	**FE**	1.37	1.40	0.13	0.11	0.20	0.27	0.30	0.26	0.08
	LB	0.85	0.89	0.27	0.37	0.31	0.1	0.291	0.31	0.17
	AT	0.19	0.30	0.18	0.14	0.20	0.15	0.23	0.13	0.12
40cpm	**FE**	0.90	0.87	0.30	0.54	0.28	0.31	0.20	0.1	0.14
	LB	0.39	0.56	0.28	0.43	0.32	0.28	0.15	0.13	0.04
	AT	0.3	0.34	0.06	0.17	0.15	0.06	0.18	0.10	0.11

*** grey shading indicates results from the primary movement direction. AOR = axis of rotation, FE = flexion-extension, LB = lateral bending, AT = axial twisting, 1 & V = IMU_1 vs. Vicon, 2 & V = IMU_2 vs. Vicon, 1 & 2 = IMU_1 vs. IMU_2, cpm = cycles/min.*

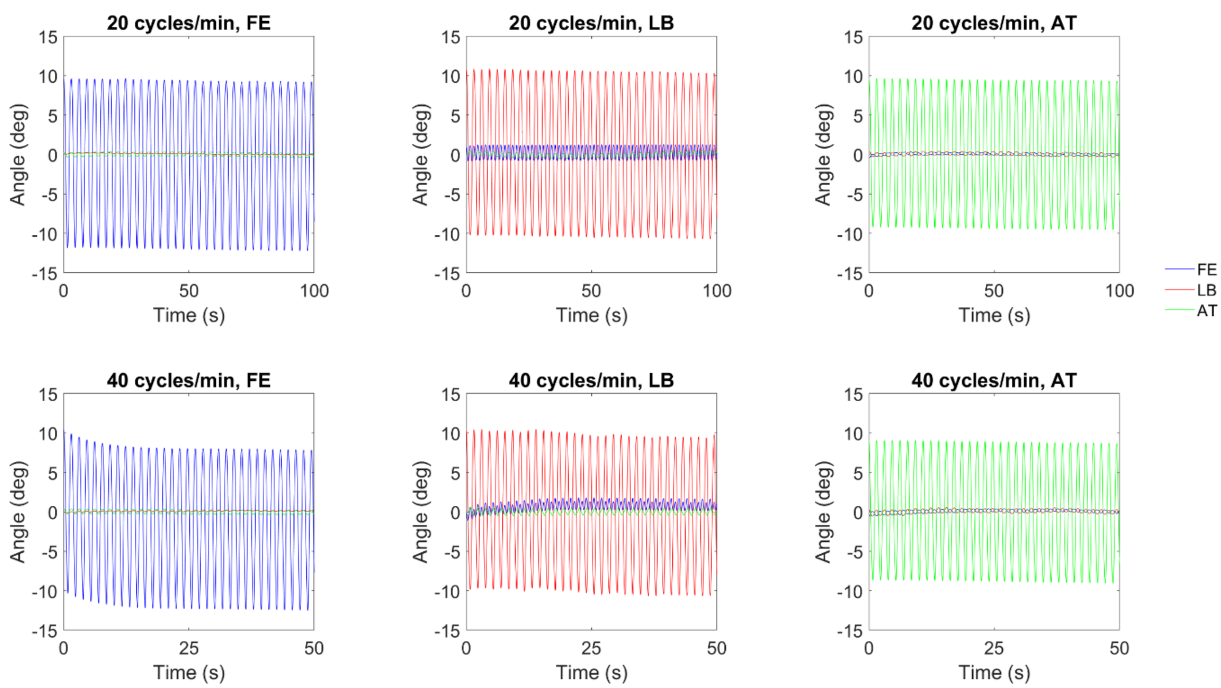


Figure 4.3. *Angular movement data from IMU_1; Flexion-Extension (FE) task (left); Lateral bending (LB) task (middle); Axial twisting (AT) task (right).*

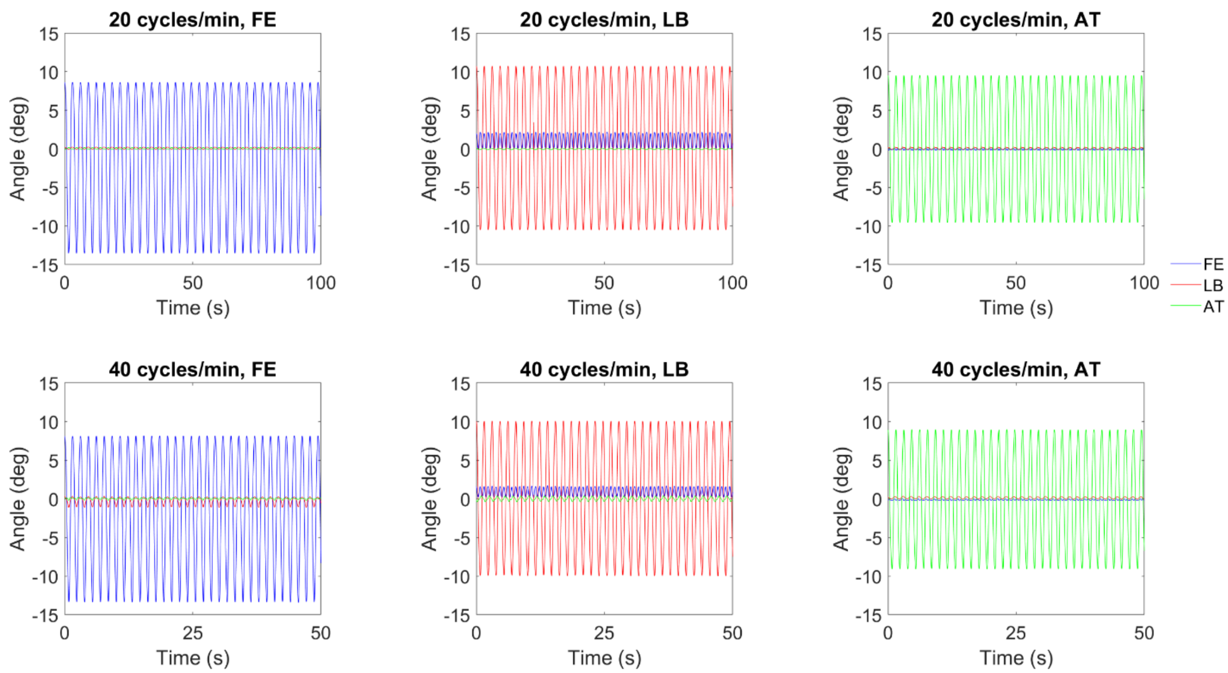


Figure 4.4. *Angular movement data from Vicon; Flexion-Extension (FE) task (left); Lateral bending (LB) task (middle); Axial twisting (AT) task (right).*

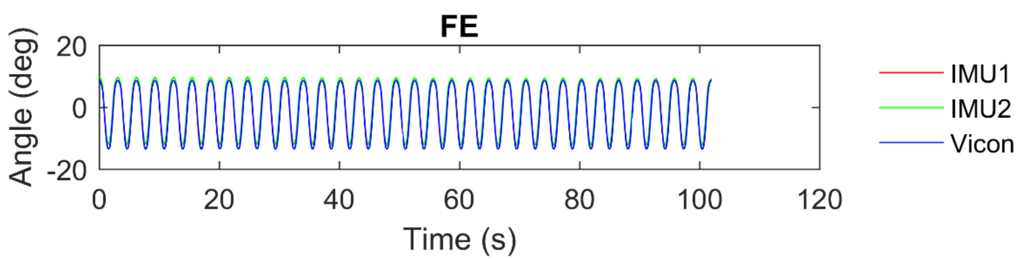


Figure 4.5. *Flexion-extension (FE) in all systems during 20 cycles/min (cpm), FE-based motion.*

4.6 Discussion

Overall the level of accuracy for the IMUs was high in comparison to Vicon and can be regarded as acceptable for use in clinical settings. Estimates of MAMD between both IMU_1 and IMU_2 with Vicon were generally similar, with low-to-moderate correlations found in one of the secondary axes of movement. These trends were apparent for all movement directions, and for both movement speeds. In addition to low MAMD within IMU_1 and IMU_2 measurements, continuous correlation values were very strong, showing repeatability of measurements.

During similar testing conditions, Ricci et al. (2016) found absolute orientation errors of up to 10.3°. In their study, level of error increased as both frequency and amplitude of movement increased (Ricci et al., 2016). The highest frequency of movement in their study was over 8 times higher than the highest frequency in this study (i.e., 40 cpm; 0.667 Hz); therefore, making direct comparison of results infeasible. Their study also placed large emphasis on orientation of the IMU in causing error. While our study found acceptable accuracy using only one orientation, this placement was chosen based on pilot testing which revealed that other orientations yielded poorer results (Appendix A). In addition, the IMUs used in the study performed by Ricci and colleagues estimated orientation based on accelerometer and gyroscope readings only, whereas the MetaMotionR sensors include magnetometer readings in the estimation process. Inclusion of magnetometer readings allows for increased accuracy in tracking orientation, but is also dependent on the corrective computational method used to compensate for influences from drift and inhomogeneous magnetic fields (Seel & Ruppin, 2017).

Though the nature of this study was designed to eliminate external sources of error, there are some limitations worth noting. While motion in the two non-primary axes of rotation should be completely restricted, the CAREN system has operational rotational limits (Barton et al., 2006), and is subject to error. It reaches these limits sooner than intended and compensates for this lack of ROM by introducing either rotation or translation in non-primary axes. The average ROM in all primary movement directions was still roughly 20°, despite being programmed to 30°, and despite this extra compensation. This ROM is lower than the 36° ROM used in the study by Ricci and colleagues, and therefore, lower MAMDs could also be a direct result of amplitude of motion. Typical human movement will usually exceed this ROM, and therefore it is worthwhile to explore larger ROMs to ensure that the low MAMD was not solely influenced by the nature of the study.

MAMD in non-primary axes was low and can be regarded as clinically acceptable. However, correlation in some axes was low. It is possible that estimates of orientation and motion tracking in non-primary axes are being affected by systematic off-axis movements evoked by the CAREN system. Because off-axis motion was to be restricted, it is also possible that these off-axis data are essentially signal noise (Volker, 2011), in which case low correlation is expected. Despite having low-to-moderate correlation in 1 of 3 axes during all movement tests, MAMD in the primary axis was always low, and correlation in the primary axis was very high during all tests. This suggests that the MetaMotionR sensors perform well when tracking motion in all axes individually, but simultaneous tracking of movement in all axes is subpar without further improved algorithms.

MetaMotionR IMUs utilize Kalman-based fusion when estimating Euler orientation; however, a further detail regarding the methods and algorithms used to provide estimates of absolute orientation is not provided. Having a more detailed description of the fusion process would allow for similar post-processing of Vicon data to match that of Mbientlab, and pin-point where IMU measurement or post-processing error is occurring (e.g., how influences from drift and inhomogeneous magnetic fields are dealt with).

In this study, we utilized one rotation sequence to generate an RHCS for the Vicon marker cluster to estimate Euler orientation, whereas the MetaMotionR IMUs operate using a left-handed coordinate system (LHCS); this could explain the poor correlation found in the third axis. Further exploration of extraction sequences for Vicon data, and for raw IMU data when aligning axes is necessary for further validation, as this has potential to introduce measurement error, and may explain the low correlations found in the second non-primary axis.

As mentioned previously, IMU validation is specific to the application that it is used for. Therefore, future studies will need to assess performance on a specific population for the desired application (e.g., evaluate performance of IMUs on the spine in LBP patients during functional movement tests). Analysis of advanced parameters that describe functional movement quality (e.g., Lyapunov exponents and continuous relative phase analyses) should also be investigated during validation on human participants to determine the degree to which primary- and off-axis movement affect these specific outcome measures.

Lastly, as previously mentioned, IMU accuracy is highly dependent on orientation (Ricci et al., 2016). There is inherent human error during sensor placement, and this is especially important when measuring accuracy of the instrument. We are currently exploring the reliability of sensor placement, as well as combinations of sensors and orientations, in congruence with corrective computational algorithms to attempt to improve on these potential errors.

4.7 Conclusion

Overall, it was shown that Mbientlab MetaMotionR IMUs have acceptable-to-excellent performance in estimating orientation and tracking motion in all axes; however, low-to-moderate correlation was found in one non-primary axis in all movement directions. Follow-up studies will investigate the effect of different fusion algorithms, extraction sequences, and IMU placement on orientation estimation and motion tracking. This study provides a framework for future work involving orientation and motion tracking using MetaMotionR IMUs in clinical populations.

5.0 ARTICLE 2: EVALUATION OF WEARABLE IMU PERFORMANCE FOR ORIENTATION TRACKING AND EVALUATION OF MOVEMENT QUALITY OF THE SPINE

5.1 Abstract

Inertial Measurement Units (IMUs) are being recognized as a portable and cost-effective alternative to motion analysis systems and have the potential to be introduced into clinical settings for assessment of low back disorders. This study was designed to assess the performance of a custom framework designed for performing IMU-based spine movement quality analyses in clinical settings using IMUs and a custom mobile application relative to conventional motion capture equipment. Ten participants performed 35 cycles of constrained repetitive trunk flexion-extension (FE) at a rate of 15 cycles/min, and lumbar spine movement data were collected simultaneously from IMUs and Vicon. Absolute Euler orientation was obtained from IMUs/marker clusters placed over T_{10}-T_{12} and S_2 spinous processes, as well as relative motion between both, and local dynamic stability was computed on both the FE data and the sum of squares (SS) of all 3-dimensional spine rotations (i.e. FE, lateral bending (LB) and axial twisting (AT)). All absolute angle results yielded a root-mean-square error of ≤ 2.43°. Pearson's correlation revealed high correlation between instruments in FE and LB planes ($0.987 \leq R_{FE} \leq 0.998$; $0.746 \leq R_{LB} \leq 0.978$); however, correlation in the AT plane was low-to-moderate ($0.343 \leq R_{AT} \leq 0.679$). Intraclass correlation between instruments when estimating local dynamic stability using both FE and SS data were high ($0.807 \leq ICC_{2,1}^{FE} \leq 0.919$; $0.738 \leq ICC_{2,1}^{SS} \leq 0.868$). It can be concluded that the IMUs have acceptable performance in all axes when tracking motion and can accurately estimate local dynamic stability using both SS and FE data; however, there is low-to-moderate correlation in one non-primary axis.

5.2 Introduction

LBP is one of the leading causes of disability worldwide, affecting over 80% of people at some point in their lifetime (Andersson, 1999). Of these cases, 85-90% are classified as non-specific (Waddell, 2004), meaning that the pain cannot be attributed to any specific injury or pathology (Dillingham, 1995). The etiology of LBP is known to be multifactorial in nature, brought on by one or more pathoanatomical, neurological, physiological, psychological, and social contributors, and therefore diagnosis and treatment of the disorder becomes unreliable and ambiguous in the majority of cases (Waddell, 1987). Because of the extremely high prevalence and difficulty of diagnosis, LBP is placing a large socioeconomic burden on health care systems worldwide. Despite the high prevalence of LBP, overall assessment and treatment of the disorder is substandard. The majority of current treatment strategies address pain and symptoms (i.e., short-term treatment) while overlooking and addressing the specific dysfunction underlying the low back disorder (i.e., long-term treatment and solution; O'Sullivan, 2005). There is a shift toward assessing spine movement quality and control to better understand and identify these underlying dysfunctions; however, visual appraisal is unreliable (Biely et al., 2014; Fritz et al., 2007; Hicks et al., 2003; Stanton et al., 2011). Therefore, researchers and clinicians are shifting toward using wearables for objective evaluation of spine motion and identification of movement-related disorders of the spine.

The use of wearables for the objective assessment of movement quality is becoming increasingly popular in clinical and rehabilitation settings to improve patient subclassification for better guidance of treatment planning (Ashouri et al., 2017). IMUs specifically are being recognized as a portable and cost-worthy alternative to conventional movement quality analysis technology (i.e., video-based optical motion capture equipment), and have the potential to be introduced into clinical settings as an objective tool to assess spine movement in LBP patients (Ashouri et al., 2017). However, uncertainties regarding sensor validity and reliability are limiting the widespread use and acceptance of IMU-based assessments into routine clinical practice (Bauer et al., 2015; Bolink et al., 2016; Cuesta-Vargas et al., 2010).

5.3 Related Work

5.3.1 Subclassification of Low Back Disorders

O'Sullivan's (2005) biopsychosocial classification system is a well-accepted method of subclassifying LBP patients based on the presence and dominance of pathoanatomical, physical, neurological, physiological, psychological, and social factors that influence the disorder. Based on the identification of these dominant factors, it is possible to determine the causal pathways between pathological pain and movement or control impairments, as well as whether the patient has adapted to the disorder in a negative manner (e.g., hypervigilance and fear avoidance behaviour, excessive stability, muscle guarding, and abnormal tissue loading; O'Sullivan, 2005). Within this classification system, there exists a large group of patients (approximately 30% of those with non-specific LBP) who suffer from movement coordination impairment (O'Sullivan, 2005). This group of low back disorders manifest in terms of altered movement quality, including excessive or poor stability, poor coordination of lumbopelvic segments, and a compensatory movement from thoracic and femoral segments. Correct identification of these movement behaviours is essential in providing appropriate intervention strategies to this group of LBP patients.

Professionals in both clinical and academic settings aim to assess spine movement quality to better understand the mechanisms underlying low back disorders; however, there is a disconnect between methods of assessment and evaluation of specific outcome measures in these domains.

Clinical assessment of LBP typically involves visual appraisal of movement quality performed by primary and allied health professionals; however, it has been shown that both inter- and intra-rater reliability are low (Biely et al., 2014; Dankaerts et al., 2006; Hicks et al., 2003; Spinelli et al., 2015). In addition, assessment in clinics typically involve self-report questionnaires, which introduces subjectivity into the diagnosis. While these questionnaires provide useful information regarding treatment-outcomes from the patients' perspective that can help guide clinical decision making, it has been shown that objective and wearable-based evaluation are better at assessing specific features associated with movement quality in experimental settings (Cook et al., 2006; Dupeyron et al., 2013; Howarth & Graham, 2015); however, it is not yet clear if it is clinically suitable. Thus, there is a need for an objective tool to be able to gather these specific outcome measures in clinical settings.

5.3.2 IMU validation

IMUs are gaining popularity in clinical and rehabilitation settings as an objective tool for assessing movement quality; however, there is a lack of translation between understanding of specific outcome measures in laboratory settings and their respective clinical application that is limiting the widespread use and integration of these methods of assessment in clinics (Whelan et al., 2016). In addition, despite extensive IMU-related research pertaining to overall IMU performance in a variety of domains, uncertainty regarding IMU measurement accuracy in comparison to conventional gold-standard motion capture equipment is contributing further to this lack of acceptance. Existing literature pertaining to IMU performance evaluation with respect to a gold-standard can be categorized broadly into two approaches: 1) assessing sensor performance in a controlled environment (e.g., on a motorized gimbal during controlled and predefined motion), and 2) assessment in uncontrolled environments (e.g., on human participants during functional movement tasks; Ricci et al., 2016). While the first approach highlights limitations inherent in the IMU by eliminating human factor sources of error, the second approach provides a more realistic validation scenario with respect to human-related applications (Ricci et al., 2016). Previous work assessing IMU performance in a controlled setting (i.e., during motion that is representative of typical spine motion, simulated by means of a controlled robotic platform) has highlighted that the IMUs have very high correlation ($R > 0.99$) and low ($RMSE \leq 1.40°$) in the primary axis of movement (Chapter 4). Low RMSE was found in all axes during motion that simulated spine FE, LB, and AT; however, low correlation was found in one non-primary axis during all tests. This suggests that the Mbientlab MetaMotionR IMUs perform well tracking motion in all axes individually, but simultaneous tracking of movement in all axes is subpar without further improved algorithms. In general, absolute error of 2° or less is considered clinically acceptable, and errors between 2° and 5° are regarded as reasonable, but may require additional subjective interpretation (McGinley et al., 2009).

Measures associated with functional movement quality are typically calculated using planar movement data, in which case poor off-axis motion tracking would both directly and indirectly affect this. Rigid plate and/or IMU local coordinate systems are intended to line up with the local anatomical coordinate system (i.e., sagittal, transverse, and frontal planes) to accurately capture motion of the specified anatomical region. Therefore, misalignment of the rigid plate and/or IMU can introduce potential measurement error as a result of trigonometric calculation incongruity when estimating absolute orientation (Taylor, Miller, & Kaufman, 2017). There are other measures (e.g., LDS) that take into consideration the sum of squares (SS) of planar movement. This is done to portray overall movement quality, as simple planar motion does not capture subsequent contraction/expansion of movement in perpendicular planes (i.e., increased movement in the frontal plane may be paired with decreased movement in the sagittal and/or transverse planes). While LDS is documented to capture overall movement and movement quality of the spine during repetitive FE (Graham et al., 2014; Graham, Sadler, et al., 2012), these estimates are heavily affected by primary-axis movement, as this motion dominates the movement. As a result, this may negate any low correlations found in non-primary axes. Estimation of λ_{max} can also be calculated using solely FE data; therefore, it is worthwhile to explore both methods to understand how primary- and off-axis motion tracking affects these measures.

A study conducted by Bauer et al. (2015) that assessed the validity of Valedo® IMUs (Hacoma AG, Switzerland) for spine motion tracking relative to gold-standard optical motion capture equipment (Vicon Motion Systems Ltd., San Francisco, USA), as well as the reliability of certain functional movement tests in evaluating spine movement quality (Bauer et al., 2015). It was determined that sagittal plane trunk movement was consistently overestimated (1.3° – 6.5°), and frontal plane movement was consistently underestimated (0.7° – 3.1°). RMSE in non-primary movement directions ranged from 1.1° – 6.8. It was deemed that the IMUs were valid for tracking trunk motion in the primary movement direction; however, performance in non-primary directions was poor. It was speculated that the lack of agreement of non-primary axis motion tracking could be a result of signal noise, limited resolution of the IMU system, potential non-linear correlations between systems, and unknown constraints on the corrective computational algorithms utilized by the on-board sensor fusion (Bauer et al., 2015). Their study also deemed that repetitive FE was not a reliable measure for identifying dysfunction and changes in performance.

Bolink and colleagues (2016) evaluated the performance of Microstrain inertia-link IMUs (LORD Microstrain, Williston, USA) compared to Vicon during selected activities of daily living (i.e., gait, sit-to-stand, block step-up). Rather than creating a localized coordinate system with Vicon in the same location as the IMU (which is what the majority of validation studies do), Bolink and colleagues (2016) used a plug-in-gait model compared directly to a single trunk IMU (located between both PSIS'; Vogt, Portscher, Brettmann, & Pfeifer, 2003). RMSE and Pearson's correlation coefficient were used to quantify error and correlation, respectively, and Bland Altman plots were used to assess level of agreement between paired measurements. RMSE fell between 2.7° – 8.89° in the sagittal plane ($0.86 \leq R \leq 0.92$), and between 2.68° – 4.44° in the frontal plane ($0.85 \leq R \leq 0.91$) for all movement tasks (Bolink et al., 2016). Bland-Altman plots revealed that level of agreement between paired measurements all fell within 2 standard deviations (SDs) of the mean, with one outlier in both sagittal and frontal ROM measurements during sit-to-stand, and in the sagittal plane ROM during block step-up.

While both of these studies yielded respectable results regarding IMU accuracy for the respective IMUs, a meta-analysis by Cuesta-Vargas and colleagues (2010) determined that the degree to which an IMU system can be deemed valid is specific to the IMU system, post-processing algorithms, and anatomical site under investigation. Therefore, it is necessary for our specific application to validate the Mbientlab MetaMotionR IMUs with the on-board sensor fusion, along with the sensor placement and movement protocol we plan to implement into our future assessments of functional movement quality of the spine.

5.4 Methodology

The University of Ottawa research ethics board has approved all ethical aspects of this research project (Appendix D).

5.4.1 Equipment and Experimental Setup

This study was designed to assess the accuracy and reliability of the MetaMotionR IMUs (maximum $80USD; Mbientlab Inc., San Francisco, USA) compared to a 10-camera passive optical motion capture system (Vicon Vantage V5 cameras; 5 megapixels; Vicon Motion Systems Ltd., Oxford, UK) during repetitive FE of the spine. MetaMotionR IMUs were adhered to two rigid plates in the configuration shown in Figure 5.1, with 4 passive reflective markers in each of the 4 corners.

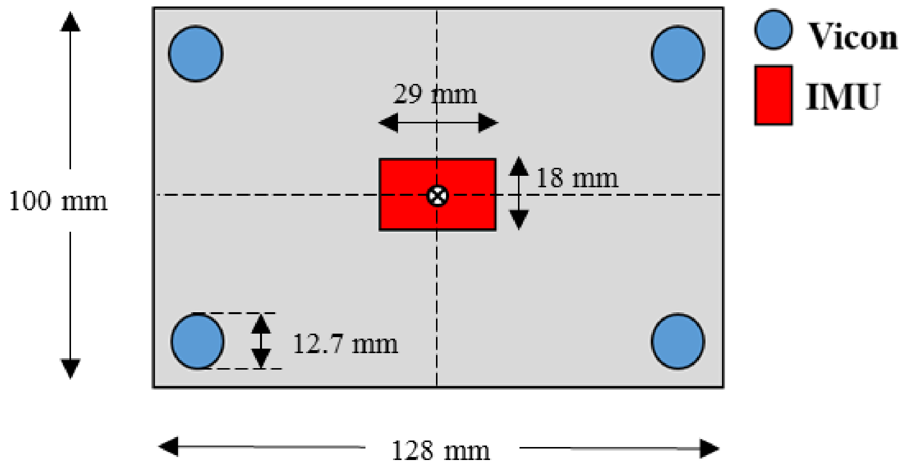


Figure 5.1. *Sensor setup and configuration.*

Rigid body marker clusters were firmly attached to the participant just over the T_{10}-T_{12} spinous processes, and over the sacrum/pelvis (S_2) using a palpation technique, as shown in Figure 5.2, and data were collected from both systems at 100 Hz. This was done to capture individual movement of each cluster/IMU pairing, and also to track the T_{10}-T_{12} cluster relative to the sacral cluster to give an overall estimate of lumbar spine motion.

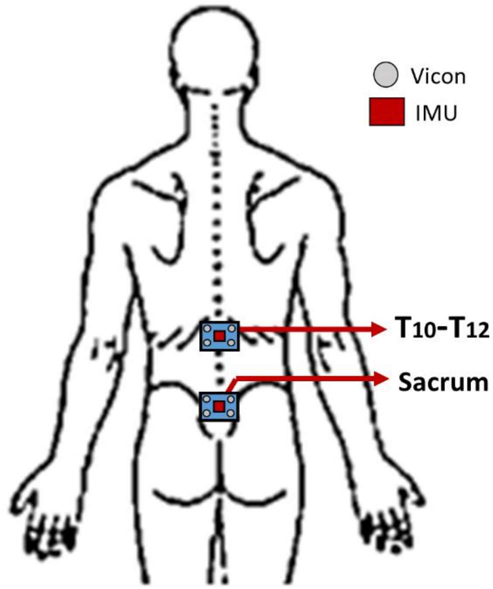


Figure 5.2. *Rigid plate/inertial measurement unit (IMU) placement.*

5.4.2 Participants and Movement Protocol

Participants were recruited via posters and word-of-mouth. Prior to participation, informed consent was obtained from all participants (Appendix E; Appendix F). Ten participants (having no history of LBP within the last 6 months) were constrained at the hip and asked to perform 35 cycles of repetitive spine FE. Participants were instructed to touch 2 targets with hands outstretched. Each target was in line with the sagittal midline, with one located at shoulder height and at arms' length away, and the other located at knee height, and positioned 50 cm anterior to the knee as shown in Figure 5.3. This task was performed in synchrony with a metronome at 30 bpm (i.e., 15 cpm; 0.5 Hz).

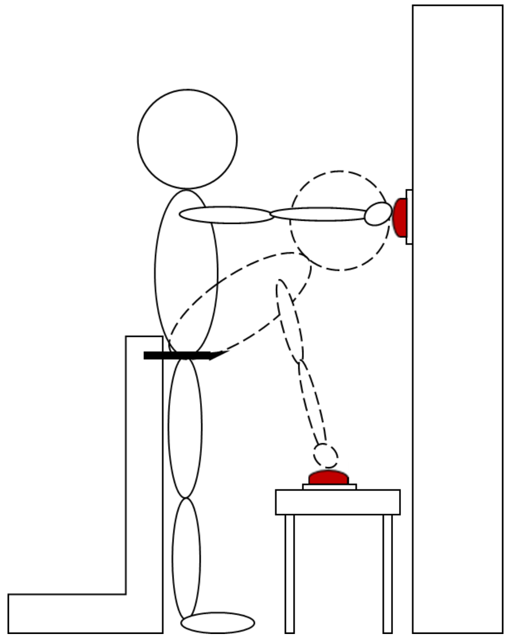


Figure 5.3. *Flexion-extension (FE) task.*

5.4.3 Data Processing and Analysis

MetaMotionR IMUs are equipped with on-board sensor fusion and are capable of outputting continuous raw sensor data, Quaternion orientation, or Euler orientation. Sensor performance was evaluated using fused Euler orientation data to enhance interpretation of results. An RHCS was generated for the Vicon rigid-body marker clusters and Euler angles were extracted using an FE-LB-AT transformation matrix rotation sequence. It is also common practice to exclude the first 5 cycles of motion to ensure steady-state motion (Graham, Sadler, et al., 2012; Granata & England, 2006) when assessing human movement quality; therefore, to ensure consistency of analyses, the last 30 cycles were analyzed. Data from Vicon and MetaMotionR IMUs were synchronized using the first peak maximum value in the sagittal plane (i.e., FE) data and low-pass filtered with a zero-phase Butterworth filter (effective 4th order with a cutoff frequency of 3 Hz) to filter out unwanted signal noise (Winter, 2010). Gyroscopic drift was removed from the

MetaMotionR IMUs by subtracting a least-squares line of best-fit from the data. Relative motion between IMUs was calculated using an FE-LB-AT rotation sequence.

Furthermore, LDS of the spine was quantified by implementing a method of time-delays to IMU and Vicon angular data in order to determine the maximum finite-time Lyapunov exponent (λ_{max}; Rosenstein et al., 1993). This process was done using both the SS of the Euler angles as well as just the sagittal FE data. The SS was calculated using equation 5.1.

$$SS_i = \sqrt{\theta_{FE_i}^2 + \theta_{LB_i}^2 + \theta_{AT_i}^2} \tag{5.1}$$

The 30 cycles of repetitive spine FE were identified for the time-series, and normalized to 12000 (30 cycles x 4 s/cycle x 100 Hz) samples (Bruijn et al., 2009b). A 6-dimensional state space for the time-series was reconstructed using a delay of 40 samples (i.e., 10% of average number of samples per cycle; Graham & Brown, 2012; Graham, Sadler, et al., 2012; Granata & England, 2006). The exponential rate of divergence between nearest neighbour trajectories in the reconstructed state space was used to estimate λ_{max}. This was done by estimating a linear line of best-fit across the first 0.5 cycles of the average logarithmic rate of divergence for all pairs of nearest neighbors using both SS and FE data (Bruijn, van Dieën, Meijer, & Beek, 2009a; Bruijn et al., 2009b; Graham, Sadler, et al., 2012; Graham, Sheppard, et al., 2012).

5.4.4 Statistical Analysis

Bland-Altman plots were used to assess level of agreement, and intraclass correlation coefficients ($ICC_{2,1}$) were applied to determine correlation of cycle-to-cycle ROM and estimates of LDS using SS and FE data. Tests for normality revealed a normal distribution in most cases; in cases where data were not normally distributed, data were transformed by taking the inverse of the data to achieve normality. RMSE was used to quantify overall error, and Pearson's correlation coefficient (R) was used to assess correlation between orientation estimates from both Vicon and MetaMotionR IMUs throughout the entire duration of the task. Any R-value above 0.7 can be regarded as a strong positive correlation, with 1.0 being perfect correlation (Cohen, 1988). Values between 0.3 and 0.7 represent weak to moderate positive correlation. These trends are the same for negative correlations, but are represented as negative values (Cohen, 1988).

5.5 Results

Table 5.1. *Participant Characteristics.*

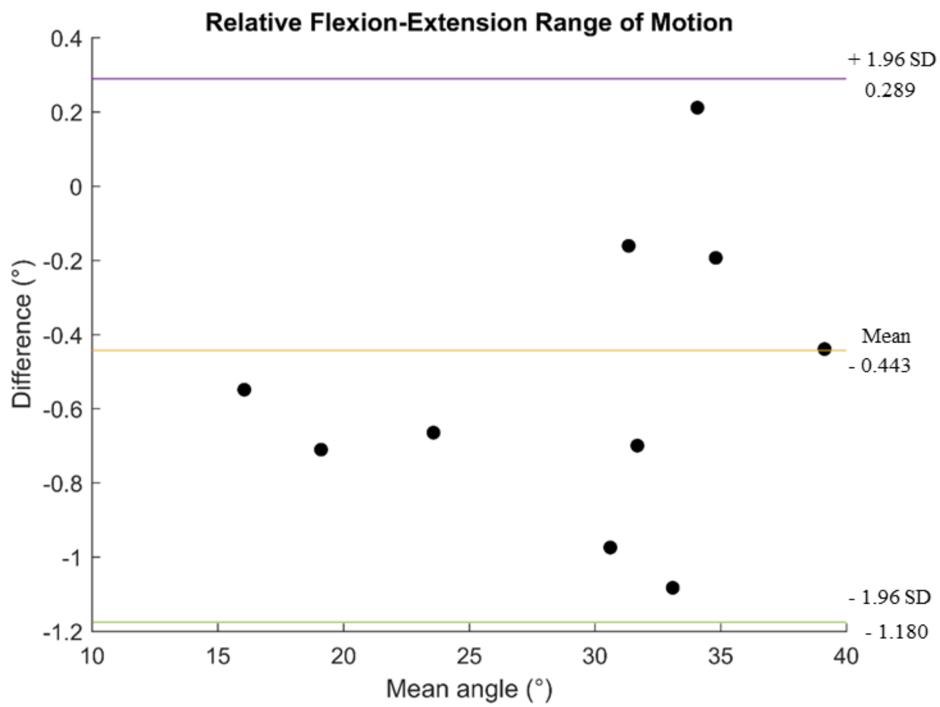
Sex	5 Male / 5 Female
Age	25.6 (2.8)
Height (cm)	174.2 (8.4)

*** Mean (SD)*

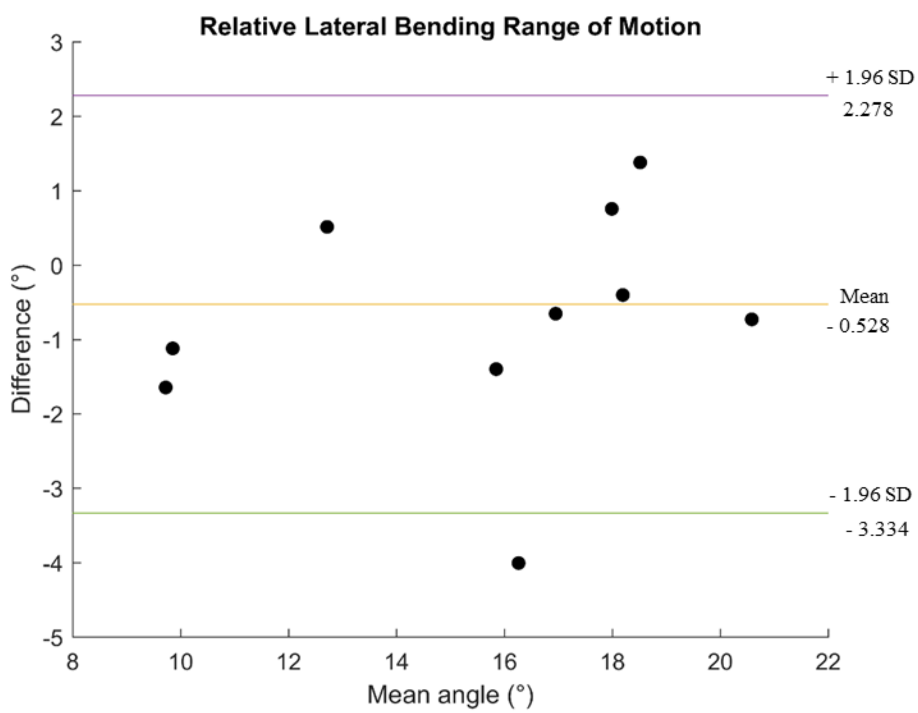
In general, strong relationships for motion tracking were found in both the FE (i.e., sagittal) and LB (i.e., frontal) planes, whereas results in the AT (i.e., transverse) plane demonstrated weaker relationships (Table 5.2). RMSE for the T_{10}-T_{12} IMU was ≤ 2.43° (with the highest error being found in the AT plane, and lowest in the LB plane). Similar trends were found in the S_2 IMU; however, overall RMSE was lower than the T_{10}-T_{12} IMU (RMSE ≤ 1.03°). Intuitively, this makes sense, as the thorax has an overall larger ROM during an FE task than the pelvis.

ROM measurements between systems were within 2 SDs of error, with one outlier found in each: T_{10}-T_{12} LB and AT plots, S_2 FE and AT plots, and LB and AT plots for relative motion. Additionally, Bland-Altman plots assessing agreement between LDS estimates revealed that differences between system estimates were within 2 SDs of error, with one outlier found in each: T_{10}-T_{12} SS and FE plots, the S_2 SS plot, and relative SS and FE plots. Bland-Altman plots illustrating level of agreement between relative ROM measurements in FE, LB, and AT planes are shown in figure 5.4; further Bland-Altman analyses are available in Appendix B.

(a)



(b)



(c)

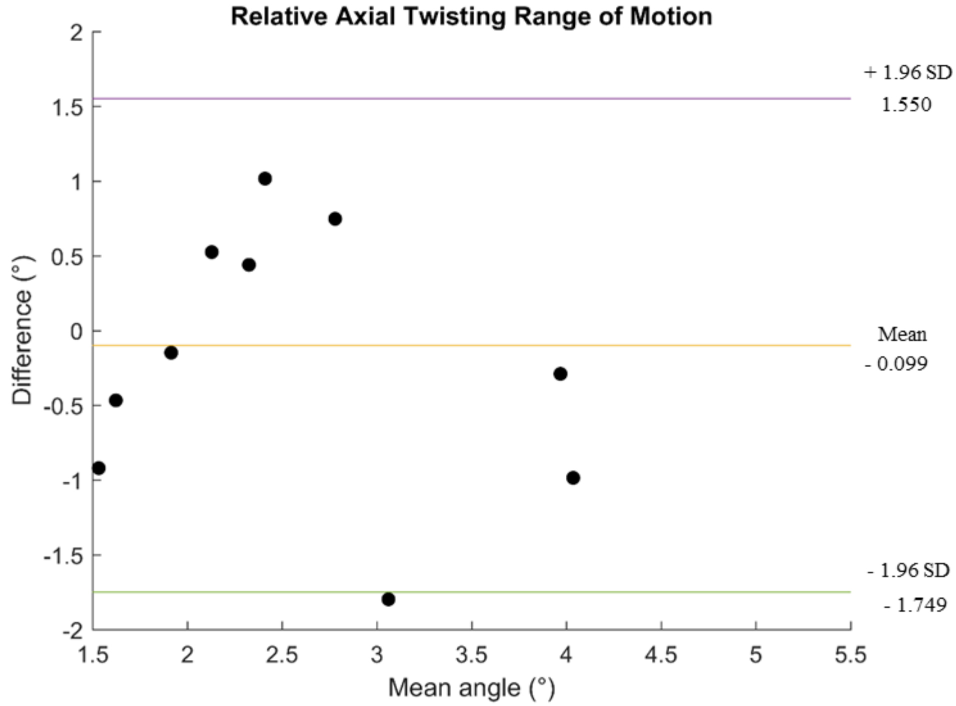


Figure 5.4. *Bland-Altman plots describing level of agreement between relative (i.e., T_{10}-T_{12} with respect to S_2) range of motion (ROM) measurements from Mbientlab MetaMotionR inertial measurement units (IMUs) and Vicon rigid body marker clusters. (a) Flexion-extension (FE). (b) Lateral bending (LB). (c) Axial twisting (AT).*

Pearson's correlation coefficient was highest in the FE plane, and lowest in the AT plane for both T_{10}-T_{12} and S_2 IMUs with their respective Vicon rigid body marker clusters. Correlation in the FE plane was ≥ 0.995 for both IMUs, and ≥ 0.746 for both IMUs in the LB plane, both of which demonstrate excellent correlational results for these axes (Table 5.2). However, the correlation in the AT axes was low-to-moderate ($R_{T_{10}-T_{12}} = 0.343$, $R_{S_2} = 0.547$; Figure 5.5.).

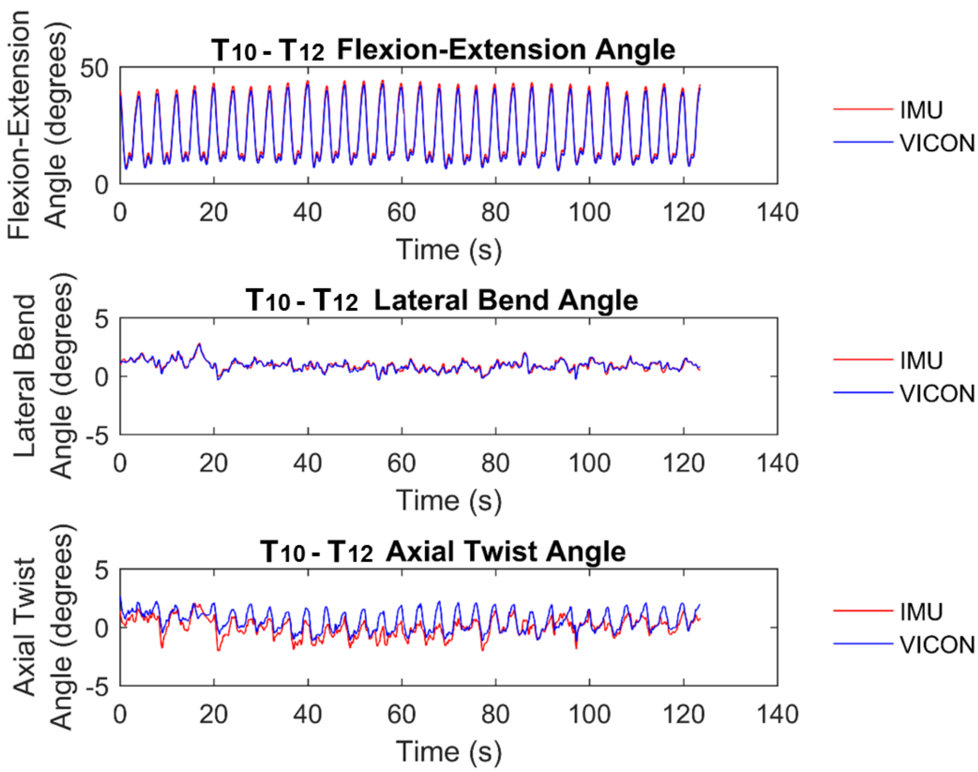


Figure 5.5. *Motion tracking of the T_{10}-T_{12} inertial measurement unit (IMU)/marker cluster during 35 cycles of repetitive flexion-extension (FE) for one participant.*

Table 5.2. *Mean (SD) and $ICC_{2,1}$ for mean cycle-to-cycle range of motion (ROM) (°) of T_{10}-T_{12} and S_2 rigid body marker cluster/inertial measurement unit (IMU) pairings, and root mean square error (RMSE) and Pearson's correlation coefficient (R) for continuous motion.*

	ROM (°)				Continuous		
	Direction	**IMU**	**VICON**	**$ICC_{2,1}$**	**Direction**	**RMSE**	**R**
T_{10}-T_{12}	FE (°)	37.8 (5.5)	37.2 (5.7)	0.999	FE	1.75	0.998
	LB (°)	2.5 (1.2)	2.5 (1.1)	0.980	LB	0.89	0.978
	AT (°)	3.7 (2.2)	2.7 (1.1)	0.356	AT	2.43	0.343
S_2	FE (°)	9.2 (3.4)	9.1 (3.3)	0.999	FE	0.89	0.987
	LB (°)	1.1 (0.4)	1.1 (0.5)	0.770	LB	0.33	0.889
	AT (°)	2.3 (1.1)	1.1 (0.9)	0.745	AT	1.03	0.547
T_{10}-T_{12} wrt S_2	FE (°)	29.6 (7.3)	29.1 (7.4)	0.999	FE	1.60	0.995
	LB (°)	3.0 (1.4)	2.2 (0.9)	0.239	LB	1.63	0.746
	AT (°)	2.2 (0.8)	2.0 (0.8)	0.559	AT	0.83	0.679

ICC: intraclass correlation coefficient; FE: flexion-extension; LB: lateral bending; AT: axial twisting; R: Pearson's correlation coefficient; wrt: with respect to, SD = standard deviation.

Intraclass correlation ($ICC_{2,1}$) analyses demonstrated excellent results when comparing mean cycle-to-cycle FE ROM values between systems (Table 5.2). Weaker relationships were found in both LB and AT planes when assessing the intraclass correlation coefficient between mean cycle-to-cycle ROM values ($0.239 \leq ICC_{2,1}^{LB} \leq 0.980$; $0.356 \leq ICC_{2,1}^{AT} \leq 0.745$).

Correlation between estimates of LDS was high when using both SS and FE data (Table 5.3). When using SS data, correlation between λ_{max} estimates for both T_{10}-T_{12} and S_2 marker cluster/IMU pairings were high ($0.738 \leq ICC_{2,1}^{SS} \leq 0.828$); however, correlation of λ_{max} between instruments when using FE data were consistently higher ($0.885 \leq ICC_{2,1}^{FE} \leq 0.919$). This trend was opposite when examining relative motion between T_{10}-T_{12} and S_2 marker cluster/IMUs ($ICC_{2,1}^{FE}$ = 0.807; $ICC_{2,1}^{SS}$= 0.868).

Table 5.3. *Mean (SD) and $ICC_{2,1}$ for local dynamic stability (LDS; λ_{max}) of T_{10}-T_{12} and S_2 rigid body marker cluster/inertial measurement unit (IMU) pairings.*

	Direction	**IMU**	**VICON**	**$ICC_{2,1}$**
T_{10}-T_{12}	FE	2.26 (0.27)	2.37 (0.28)	0.919
	SS	2.11 (0.22)	2.25 (0.26)	0.828
S_2	FE	1.88 (0.18)	1.96 (0.28)	0.885
	SS	1.80 (0.20)	1.93 (0.28)	0.738
T_{10}-T_{12} wrt S_2	FE	2.13 (0.24)	2.33 (0.22)	0.807
	SS	2.10 (0.19)	2.29 (0.19)	0.868

ICC: intraclass correlation coefficient; FE: flexion-extension; SS: sum of squares; wrt: with respect to.

5.6 Discussion

Overall, IMU accuracy in measuring absolute orientation can be regarded as clinically acceptable (i.e., RMSE ≤ 2°) in both the FE and LB planes, and acceptable, but may require additional interpretation (i.e., 2° < RMSE ≤ 5°) in the AT plane. This lines up well with what Bauer and colleagues found during their validation study, where it was deemed that the IMUs were valid for tracking trunk motion in the primary movement direction; however, performance in non-primary directions was suboptimal (Bauer et al., 2015). When reviewing intraclass correlation coefficients for mean cycle-to-cycle ROM, strong positive correlations were found in the FE axis, with weaker relationships being found in LB, and AT axes. Cycles in all axes were separated based on peaks found in the FE data; while the nature of this study was designed to restrict motion in LB and AT axes, natural spine motion in 1-dimension (e.g., FE) is typically paired with expansion/contraction in other axes (e.g., LB and AT; Gates & Dingwell, 2009; Granata & England, 2006). With that being said, motion in non-primary axes did not demonstrate the same degree of cyclic behaviour as the primary-axis motion, which could explain the low-to-moderate correlations in the non-primary axes for the measurement of ROM. In addition, mean absolute motion in non-primary axes did not exceed 3.7°; thus, very small off-axis movements (e.g., internal perturbations that are inherent within the spinal control system) could drastically affect the magnitude of the ROM values in these axes.

Pearson's correlation coefficient results were high in both FE and LB planes ($0.987 \leq R_{FE} \leq 0.998$; $0.746 \leq R_{LB} \leq 0.978$); however, correlation in the AT plane was low-to-moderate ($0.343 \leq R_{AT} \leq 0.679$). Participants were instructed to restrict their motion to the FE plane, potentially explaining the low error in both LB and AT planes (i.e., on average, motion in these planes did not exceed 4°, and therefore low absolute error is to be expected). At the same time, because off-axis motion was intended to be minimized, the IMU data could just be a result of signal noise, in which case low correlation is to be expected (Volker, 2011); however, this would only explain low correlation if it occurred in both LB and AT planes. Bauer and colleagues (2015) speculated that this lack of agreement of non-primary axis motion tracking could also be a result of potential non-linear correlations between systems, and unknown constraints on the corrective computational algorithms utilized by the on-board sensor fusion. It is known that the MetaMotionR IMUs utilize Kalman-based fusion to predict orientation from raw accelerometer, gyroscope, and magnetometer data; however, the details pertaining to how influences from gyroscopic drift, inhomogeneous magnetic fields, and signal noise etc. are dealt with are unknown, making the fusion process somewhat of a "black box" process. Having a more detailed description of the corrective computational algorithms could allow us to match Vicon post-processing methods, and pin-point where processing error is occurring. Moreover, once these incongruencies are identified and understood, it can be determined whether there are non-linear relationships between the systems that may explain the low correlations. The MetaMotionR IMUs also utilize an LHCS, whereas the Euler orientation obtained for the Vicon system was extracted using an RHCS, which could explain lower correlations in the AT axis. We are currently exploring creating an LHCS for Vicon data, as well as various extraction sequences to see if this will minimize any error that is occurring.

The MetaMotionR IMUs also show high correlation with Vicon data in measuring LDS. There was higher correlation for LDS when using solely FE data compared to LDS using the SS for individual IMUs and rigid-body marker clusters. This is likely due to the fact that the lower correlations in the AT plane data would affect the overall calculation of the SS. With that said, because the motion is heavily dominated by FE motion, the low-to-moderately correlated non-primary axis does not have a large influence on the calculation of the SS and is outweighed by the large-amplitude FE plane data. λ_{max} estimates for relative motion between IMUs/marker clusters on the other hand demonstrate contrasting results, whereas higher correlation between instruments is found when using SS data, rather than FE data (though both were still high). This likely has something to do with concurrent expansion/contraction in non-primary axes during FE-based movement; that is, while *individual* IMUs/marker clusters show higher correlation between primary-axis motion and estimates of λ_{max}, *relative* primary-axis motion may demonstrate lower correlation, as small off-axis motion (i.e., concurrent expansion/contraction) that contribute to the SS can be negated. Obtaining the *relative* SS of the movement can essentially wash this out, as it is a more comprehensive representation of the motion. Overall, LDS was estimated with high accuracy using both SS and FE data, and therefore the MetaMotionR IMUs can be considered accurate in quantitatively assessing spine movement quality despite having low-to-moderate correlation in one non-primary axis, and can be used as a clinical tool for the evaluation of movement quality (i.e., LDS) during 1-dimensional rotational motion.

Future studies should explore different movement directions in human participants (e.g., 35 cycles of repetitive lateral bending and axial twisting), as well as combinations of movements (e.g., repetitive multiplanar movement) to understand how primary- and off-axis movement affects motion tracking and estimates of LDS. It would also be interesting to look at additional parameters associated with spine movement quality, such as coordination and variability (determined using continuous relative phase analyses) to improve the database of clinical tests that are deemed reliable and/or appropriate for assessing spine movement quality using wearable IMUs. Based on our previous study, it is expected that there would be high correlation in the primary direction of movement, and one secondary axis, with low correlation in the last axis (Chapter 4). For this reason, evaluating performance during repetitive multi-planar movements may reveal how each axis is affected. It is understood that movement coordination impairment typically presents in a directional manner, and, therefore, it would be ideal to be able to assess movement quality in a variety of directions (O'Sullivan, 2005). For example, assessing one's stability during solely FE motion may not yield the same results as if their stability was assessed during LB or AT directed motion (O'Sullivan, 2005). Lastly, future work should explore reliability testing for IMU placement, as well as combinations of IMUs and IMU orientations in congruence with corrective computational algorithms to minimize error.

5.7 Conclusion

Overall, MetaMotionR IMUs can be regarded as acceptable for clinical use. Despite low-to-moderate correlation in one non-primary axis, LDS can still be accurately estimated using both SS and FE data. Future studies should evaluate performance during multi-planar movement to determine the degree to which off-axis motion tracking affects the quantification of spine movement quality. Refinement of the IMU post-processing algorithms is necessary for overall validation of the sensors for clinical use.

6.0 GENERAL DISCUSSION

This work assessed the performance of Mbientlab MetaMotionR IMUs relative to gold-standard Vicon motion capture equipment in both controlled, and uncontrolled environments with the main goal of assessing spine movement quality in people with LBP. The first study involved an assessment of performance of the IMUs during controlled, repetitive sinusoidal motion, and revealed that the IMUs can be regarded as accurate in tracking motion in all three axes, with the exception of low-to-moderate correlation in one non-primary axis (Chapter 4). In this study, MAMD and RMSE were low in all axes during motion that simulated spine FE, LB, and AT at frequencies of 20 cpm and 40 cpm (i.e., 0.33 Hz and 0.67 Hz, respectively). There was excellent correlation between MetaMotionR IMUs and Vicon in the primary axis of rotation and one non-primary axis; however, low-to-moderate correlation was found in the last non-primary axis during all tests, and this axis changed depending on the direction of the movement. There was extremely high correlation in the primary axis of rotation for all movement directions, which suggests that the sensors are adequate at tracking motion in all three planes but lack the ability to achieve high correlation in all axes simultaneously. This likely has something to do with the extraction sequences and/or fusion algorithms used for either MetaMotionR IMUs or Vicon, or both. Because the on-board sensor fusion process utilized by Mbientlab is unknown, the process becomes somewhat of a “black box”, whereas the inputs and outputs are known (i.e., movement tracking via raw sensor data, and Euler orientations, respectively); however, the corrective computational fusion algorithms used to get from point A to B are unknown. It is known that the MetaMotionR IMUs utilize “Kalman-based fusion” to predict orientation from raw accelerometer, gyroscope, and magnetometer data; however, the details pertaining to how influences from gyroscopic drift, inhomogeneous magnetic fields, and signal noise etc. are dealt with. Having a more detailed description of these corrective computational algorithms could allow us to match Vicon post-processing methods, and also pin-point where processing error is occurring. Bauer and colleagues (2015) suggested that the lack of agreement in the third non-primary axis found in their study could be a result of potential non-linear correlations between systems. Once incongruences in the fusion process are identified and understood, it can be determined whether there are non-linear relationships between the systems that may explain the third-axis low correlations. The MetaMotionR IMUs also utilize an LHCS in estimating orientation, whereas the Euler orientation obtained for the Vicon system was extracted using an RHCS, and could explain the low correlation found in the third non-primary axis. We are currently exploring LHCSs, in correspondence with various extraction sequences to attempt to optimize sensor performance in all axes.

In the first study, the poorer performing axis differed depending on the direction of movement of the CAREN platform: during FE-based motion, low correlation was found in the LB plane; during LB-based motion, low correlation was found in the AT plane; and during AT-based motion, low correlation was found in the FE plane. This trend carried over to the second study, whereas performance of the MetaMotionR IMUs was assessed relative to Vicon during repetitive, constrained FE of the lumbar spine in 10 participants (Chapter 5). In this study, RMSE and Pearson's correlation coefficient were used to evaluate level of agreement between IMUs and Vicon for continuous motion, and intraclass correlation coefficients were used to determine correlation between cycle-to-cycle ROM and LDS estimates for both systems. RMSE was low (i.e., < 2°) in 2 axes and therefore can be regarded as "acceptable for clinical use," while one non-primary axis had an RMSE of 2.43°, which is "acceptable" but may require additional subjective interpretation (McGinley et al., 2009). Similar to the first study, this study found very high correlation in the primary axis of rotation and one non-primary axis, and low-to-moderate correlation in the third non-primary axis. Contrary to the first study, which showed low-to-moderate correlation in the LB axis during FE directed movements, FE-based motion during this study was paired with a low-to-moderate correlation in the AT plane.

Motion in both the first and second study (Chapters 4 and 5, respectively) were restricted to one plane, which may explain the low error found in both non-primary axes, as the movement itself should be minimal. At the same time, because motion in the non-primary axes was supposed to be minimized, the low correlation in the one non-primary axis could essentially be signal noise, in which case low correlation is to be expected; however, this argument would be stronger if lower correlations were found in both LB and AT planes, not just one or the other. Determining the signal-to-noise ratio in future studies may help to understand this relationship. It is likely that signal noise is contributing to low-to-moderate correlations found in Chapter 4; Chapter 5 on the other hand has additional factors that likely contribute to this (i.e., human factors sources of error). It is known that motion of the spine in 1-dimension (e.g., FE) is typically paired with expansion/contraction in other axes (e.g., LB and AT; Gates & Dingwell, 2009; Granata & England, 2006). Motion in non-primary axes in Chapter 5 did not demonstrate the same degree of cyclic behaviour as the primary-axis motion, which could explain the low correlation in the non-primary axes when comparing mean cycle-to-cycle ROM. On top of this, on average, absolute motion in non-primary axes was very low (i.e., $\leq 3.7°$); thus, very small off-axis movements (e.g., internal perturbations that are inherent in the spine control system) could drastically affect the magnitude of the ROM values in these axes. It was therefore concluded that RMSE and Pearson's correlation coefficient are better parameters at assessing performance of the IMUs relative to Vicon in uncontrolled environments. The study conducted by Bauer and colleagues (2015) in which IMU performance was assessed relative to gold-standard passive optical motion capture during various tasks involving trunk motion also concluded that the IMUs perform well in 2 of 3 axes. However, the movement protocol performed in Bauer's study (2015) involved movements that were not just restricted to one plane, and, therefore, it is more likely that there are incongruences in the fusion process for both MetaMotionR IMUs, as well as the IMUs utilized by Bauer and colleagues (2015), rather than just signal noise. Their study also tested the reliability of certain movement tests for assessing overall movement quality of the lumbopelvic region, and found that repetitive FE was not a reliable test to capture changes associated with injury or rehabilitation (Bauer et al., 2015). However, the protocol for repetitive FE used by Bauer et al. (2015) was drastically different than ours – a method that has been extensively used in previous work to measure LDS of the spine, and has been documented to capture differences in pathological versus healthy control groups (e.g., Graham et al., 2014; Ross et al., 2015).

During testing conditions similar to that of the first study (Chapter 4), Ricci et al. (2016) found absolute orientation errors of up to 10.3°. They found that the level of error increased as both frequency and amplitude of movement increased (Ricci et al., 2016). Our first study, which involved 2 different movement frequencies did not reveal these trends; however, the highest frequency of movement in the Ricci study was more than 8 times higher than our highest frequency, and ROM was 36° whereas the motorized platform only reached a ROM of 20°, making direct comparison of results impractical. While Ricci et al. (2016) reported increasing error with increasing frequency, this relationship is generally not relevant for our application, as the patients will not be asked to perform movements at high frequencies. During our second study (Chapter 5), participants exhibited a ROM of roughly 37° (as measured by both IMUs and Vicon), and still found very high accuracy and correlation in the primary axis of rotation and one secondary axis. To test this, error as a percentage of overall ROM was calculated in all axes (equation 6.1 – 6.3).

$$\%_{error}^{FE} = \frac{RMSE_{FE}}{ROM_{FE}} \times 100 \tag{6.1}$$

$$\%_{error}^{LB} = \frac{RMSE_{LB}}{ROM_{LB}} \times 100 \tag{6.2}$$

$$\%_{error}^{AT} = \frac{RMSE_{AT}}{ROM_{AT}} \times 100 \tag{6.3}$$

This revealed that level of error in the primary axis (i.e., FE; highest ROM) is low (i.e., $\%_{error}^{FE} =$ 4.6% – 9.7%), error in the second non-primary axis (i.e., LB) is low, but as a percentage of the ROM, is higher than in FE (i.e., $\%_{error}^{LB} =$ 30.0% - 63.0%), and error in the third non-primary axis is high as a percentage of the total ROM (i.e., $\%_{error}^{AT} =$ 40.0% - 76.0%). Thus, it can be said that absolute error is *not* affected by the amplitude of the movement itself, and that low-to-moderate correlation in the third non-primary axis is most likely a result of the on-board fusion process utilized by the on-board sensor fusion and/or extraction sequences/lining up of coordinate systems between Mbeintlab and Vicon systems. Ricci and colleagues also placed large emphasis on orientation of the IMU in causing error (Ricci et al., 2016). While this may be true, previous pilot work confirmed optimal sensor placement for both studies in this thesis. However, we are still exploring reliability of IMU placement, as well as combinations of IMUs and IMU orientations in order to optimize overall performance for the evaluation of spine movement quality.

When considering the evaluation of spine movement quality, the MetaMotionR IMUs show high correlation with Vicon data in measuring LDS using both FE and SS data, as demonstrated in the second study. Correlation was higher for individual IMUs/marker clusters when using FE data compare to the SS. This likely has something to do with the lower correlations found in the AT plane, which affect the calculation of the SS; however, because the motion is heavily dominated by FE motion, the lower correlated AT axis does not have a large influence on the calculation of the SS, thus, both produced excellent correlations. Correlation between LDS estimates for relative motion between IMUs/marker clusters on the other hand demonstrate contrasting results, whereas higher correlation between instruments is found when using SS data, rather than FE data (though both, again, were still high). It is likely that this has something to do with concurrent expansion/contraction in non-primary axes during FE-based movement; that is, *individual* IMUs/marker clusters show higher correlation between primary-axis motion and estimates of LDS because weaker correlations in non-primary axes are omitted. Correlations between *relative* primary-axis motion and estimates of LDS may be lower, as the small off-axis movements (i.e., concurrent expansion/contraction) that contributes to the SS are annulled and do not provide a comprehensive representation of the motion. Altogether, correlations between Mbientlab and Vicon estimations of LDS were high, and therefore the MetaMotionR IMUs can be considered accurate in measuring spine movement quality despite low-to-moderate correlation in one non-primary axis and can be used as a clinical tool for the evaluation of movement quality (i.e., LDS) during 1-dimensional rotational motion. However, this is not entirely realistic moving forward. It is understood that movement coordination impairment typically presents in a directional manner, and, therefore, it would be ideal to be able to assess movement quality in a variety of directions (O'Sullivan, 2005). Future studies should explore various movement directions in human participants. (e.g., 35 cycles of repetitive LB and AT), as well as combinations of movements (e.g., repetitive multiplanar movement) to gain more insight on how primary- and off-axis movement affects motion tracking and estimates of LDS. In additions, assessing one's stability during solely FE motion may not yield the same results as if their stability was assessed during LB or AT directed motion (O'Sullivan, 2005), depending on how their LBP has manifested; therefore, these types of analyses have potential to provide input into individual low back disorders. It would also be interesting to explore additional parameters associated with spine movement quality, such as coordination and variability (determined using continuous relative phase analyses) of thoracic, lumbar, and pelvic regions to improve the database of clinical tests that are deemed accurate and/or appropriate for assessing spine movement quality using MetaMotionR IMUs. Similar to Bauer and colleagues (2015), it would be necessary to perform reliability analyses on the suggested tasks and specific outcome measures in the assessment of spine movement quality, and that is something we are looking into doing.

MetaMotionR IMUs are equipped with on-board sensor fusion and are capable of outputting either Euler or Quaternion orientation. Obtaining Quaternion orientation eliminates the issues of singularity and of gimbal lock (Jung et al., 2013; Lepetit & Fua, 2005; Mitchell & Rogers, 1965); however, it is not as easily interpretable as Euler orientation. Future studies should explore obtaining both individual and relative Quaternion orientations via on-board sensor fusion and converting to Euler orientations to see if error in the third non-primary axis a result of incongruencies within the Euler fusion algorithms. Another option moving forward is to implement custom filtering/fusion algorithms in order to understand and control exactly what is occurring to obtain absolute Euler orientation from raw accelerometer, gyroscope, and magnetometer data. Fusion techniques by Madgwick and colleagues are available to implement and customize if required (Madgwick et al., 2011), and are, therefore, a good starting point. In addition to custom fusion processes, we are currently exploring various supervised machine learning methods to predict IMU orientation – i.e., we *know* what the data outputs *should be* by considering Vicon data to be gold-standard, and, therefore, we can *train* a set of algorithms to *predict* accurate orientation.

It is also possible that, despite optimization of conditions for motion tracking using Mbientlab MetaMotionR IMUs, these sensors do not perform to the same standard as optical motion capture equipment. However, while results from Chapters 4 and 5 revealed low-to-moderate correlation in one non-primary axis, this does not necessarily mean that these results are undesirable for our intended application. MetaMotionR IMUs were still able to capture aspects of spine movement quality and control (i.e., LDS, λ_{max}), yielding very high correlation with respect to Vicon optical motion capture. Moving forward, it is not only necessary to specify limits of what is considered acceptable for tracking motion (e.g., RMSE $\leq 2°$, or $2° \leq$ RMSE $\leq 5°$ for absolute angle estimation), but also what is acceptable for the desired application (e.g., LDS and other specific outcome measures that quantify aspects of spine movement quality and control).

Overall, this work provides a solid foundation of understanding for motion tracking using Mbientlab MetaMotionR IMUs and has provided us with a framework moving forward to further assess and optimize performance of the IMUs for motion tracking and assessment of spine movement quality in clinical settings. Before proceeding, limits of what is acceptable when assessing performance for quantifying aspects related to spine movement quality must be stated.

7.0 GENERAL CONCLUSION AND FUTURE WORK

7.1 General Conclusion

This work assessed the performance of Mbientlab MetaMotionR IMUs for orientation estimation and motion tracking relative to gold-standard video-based passive optical motion capture under both controlled (Chapter 4), and uncontrolled (Chapter 5) conditions. Performance in estimating LDS of the spine was also evaluated in the uncontrolled condition (Chapter 5). Both studies confirmed that the MetaMotionR IMUs perform well in all axes for motion tracking. Despite low-to-moderate correlational results in one non-primary axis, LDS can still be accurately estimated using both the SS and FE-based motion. Therefore, MetaMotionR IMUs can be used as a clinical tool for tracking absolute motion and measuring LDS of the spine during 1-dimensional planar motion. This thesis acts as a fundamental step towards incorporating wearables for objective assessment into clinical and rehabilitation settings.

7.2 Future Work

Future studies will explore: multiplanar movement and the effect on primary and non-primary axis motion tracking; combinations of sensors and orientations in congruence with custom fusion and corrective computational algorithms to minimize error; different extraction sequences and methods of lining up coordinate systems; and reliability of sensor placement for evaluation of spine motion and spine movement quality. Before proceeding, limits of what is acceptable when assessing IMU performance for the quantification of specific outcome measures related to spine movement quality should be specified. Future study details are described below:

Study 1: Exploration of orientation representations and post-processing methods.

Because pilot testing revealed that obtaining Euler orientation directly from the Mbientlab MetaMotionR on-board sensor fusion brought up several issues (i.e., gimbal lock, gyroscopic drift, orientation incongruences, cross-quadrant jumping, low-to-moderate correlation in one axis), a future study will explore collecting orientation data using other representations; more specifically, Quaternion orientation and raw accelerometer, gyroscope, and magnetometer data will be collected. In this study, data will be collected from 3 adjacent IMUs via 3 separate mobile-based applications, where one will collect Quaternion orientation, one will collect Euler orientation, and the last will collect raw sensor data (this must be done using 3 separate applications because it is impossible to collect all three orientation representations using only 1). The study will involve repetitive rotational motion, in which each trial will test a different IMU orientation (i.e., IMUs will be rotated 90° to isolate FE, LB, and AT axes – similar to Chapter 4). Raw sensor data will undergo custom fusion processes to obtain Euler orientation, and Quaternion data will be transformed into Euler orientation to reveal the optimal data collection technique.

There will be one subsequent study in which the data collection method will remain the same as listed above. This study will involve data collection from 9 IMUs (3 per mobile application); each mobile application will collect data from 3 IMUs in a configuration that isolates FE, LB, and AT axes simultaneously, throughout repetitive rotational motion. Both of these studies will also test various extraction sequences for obtaining Euler orientation from Quaternions and raw data, and for obtaining relative orientation between sensors.

Study 2: Reliability assessment and misalignment testing.

This study will be designed to evaluate the reliability of MetaMotionR IMUs for motion tracking and calculation of specific outcome measures related to movement quality of the spine, as well as the robustness to misplacement/misalignment. IMUs will be adhered to a rigid plate with varying degrees of offset and duplicated to assess reliability (Figure 7.1).

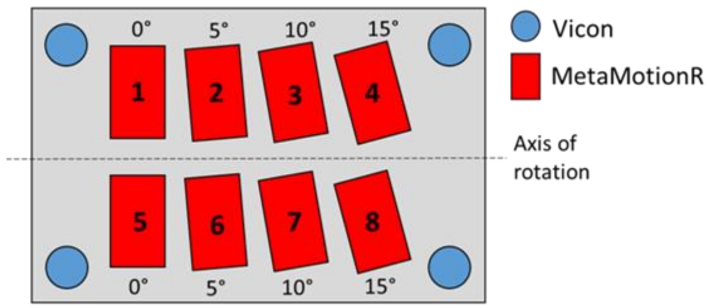


Figure 7.1. *Inertial measurement unit (IMU) configuration for testing of IMU reliability and robustness to misalignment.*

Study 3: New movement protocol.

Chapters 4 and 5 revealed that the MetaMotionR IMUs perform well (i.e., low RMSE, high correlation) in two of three axes, and that the third 'poorer-performing' (i.e., low-to-moderate correlation) axis changed based on the direction of the motion (Chapter 4); based on these results, it is necessary to explore a variety of movement directions in human participants (e.g., 35 cycles of repetitive FE, LB, and AT), as well as combinations of movements (e.g., repetitive multiplanar movement) to understand how primary- and off-axis movement affects motion tracking and estimates of LDS (figure 7.2). Based on results from Chapter 4, the axis with low-to-moderate correlation will change depending on the primary movement direction of the test; however, multiplanar movement where motion is not restricted to 1 plane will reveal how the IMUs perform in different testing conditions. Additional specific outcome measures used to quantify aspects of spine movement quality and control will be calculated and compared using the same statistical methods in Chapter 5; reliability tests will also be performed to reveal how reliable each task and/or calculation of specific outcome measure is.

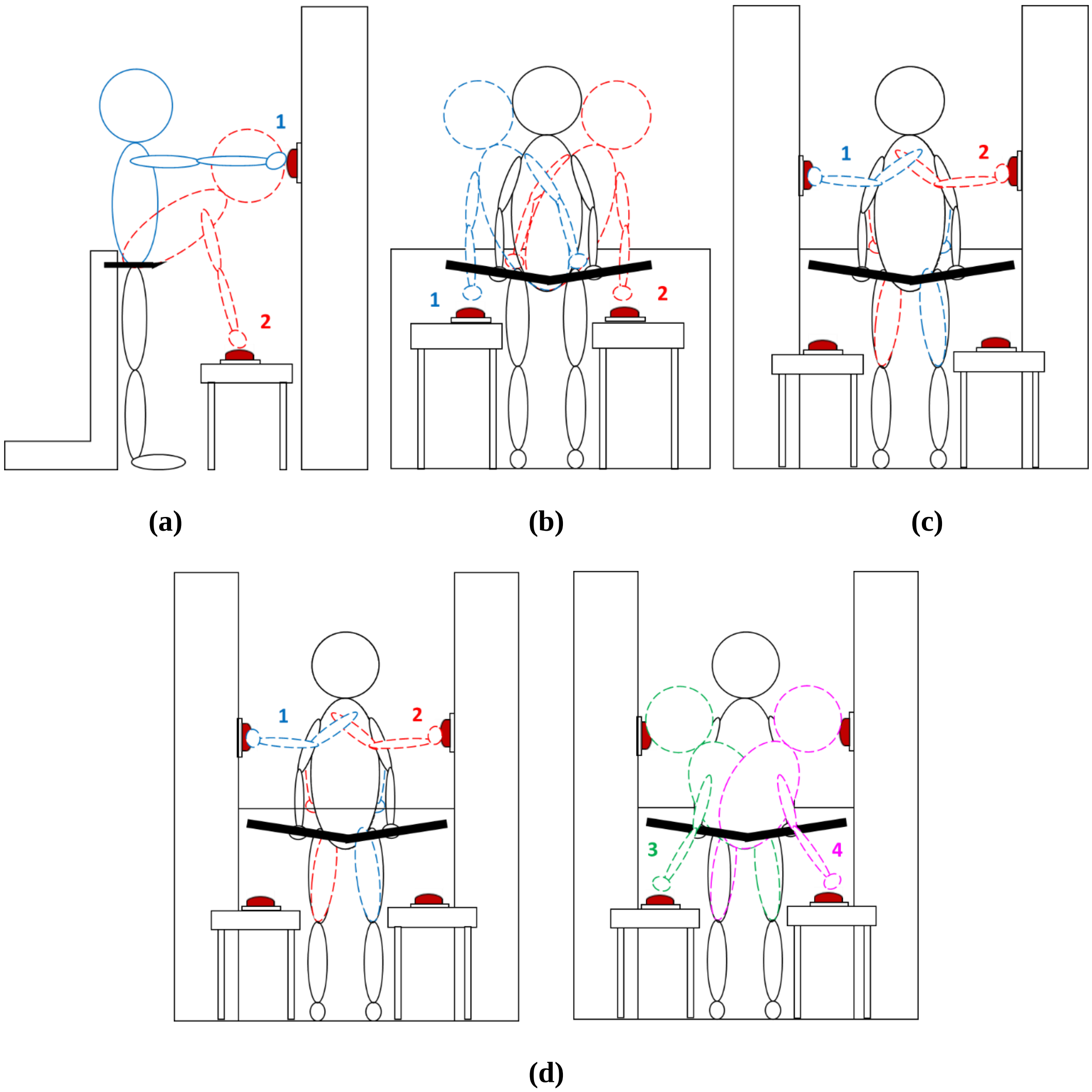


Figure 7.2. *Example of various multi-directional movement tasks. (a) Flexion-extension (FE). (b) Lateral bending (LB). (c) Axial twisting (AT). (d) Multi-directional complex task.*

Study 4: Machine learning.

We are currently exploring various supervised machine learning methods to predict IMU orientation – i.e., we *know* what the data outputs *should be* by treating Vicon data as the gold-standard, and, therefore, we can *train* a set of algorithms to *predict* accurate IMU orientation. This study will be done using the optimal orientation representation revealed in study 2 (Chapter 7).

8.0 MAJOR CONTRIBUTIONS

This thesis involves contributions from two major studies that are part of an on-going, overarching project. The main goal of the on-going project is to create a framework for performing objective spine movement quality assessment in clinical settings for patients with non-specific LBP; the secondary goal is to subclassify the LBP population based on individual movement profiles in order to identify the underlying mechanism that is driving their low back disorder. More specifically, the framework involves the use of wearable IMUs and a custom mobile-based application paired with cloud-computing. The application is designed to provide a clinician with objective measures that identify and classify particular movement profiles in LBP patients in order to provide appropriate rehabilitation programs that target individual impairments.

The main contributions of this thesis primarily involve the assessment of the performance of the MetaMotionR IMU for motion tracking and evaluation of movement quality of the spine relative to conventional optical motion capture equipment. More specifically, the main contributions are:

1. **Determination of optimal conditions for tracking motion using MetaMotionR IMUs (Appendix A).**

Through extensive piloting, the optimal conditions for MetaMotionR IMU data acquisition and interpretation were determined. More specifically, performance was optimized by: discovering the most ideal IMU orientation for tracking motion; determining the most effective platform and/or techniques for data acquisition; and discovering the best computational post-processing methods to enhance interpretation and allow for comparison of results between Mbientlab and Vicon motion capture systems.

2. **Evaluation of Mbientlab MetaMotionR IMU performance for orientation estimation and motion tracking in a controlled environment (Chapter 4).**

It was determined that the MetaMotionR IMUs perform well tracking motion all axes (MAMD $\leq$ 1.54°; RMSE $\leq$ 1.40°); however, low-to-moderate correlation was found in one non-primary axis, and this lower-correlated axis changed depending on the direction of movement (i.e., FE during AT-motion, LB during FE-motion, and AT during LB-motion). It was therefore concluded that the MetaMotionR IMUs have acceptable performance in all axes when tracking motion; however, they lack the ability obtain high correlation in all axes simultaneously. It is possible that this could be a result of either signal noise (because the motion in the non-primary axis of motion is supposed to be restricted/minimized – in which case low correlation is to be expected); however, it is more likely that this is a result of the on-board sensor fusion methods used when computing Euler orientation.

3. **Evaluation of Mbientlab MetaMotionR IMU performance for motion tracking and assessment of spine movement quality in an uncontrolled environment (Chapter 5).**

It was determined that, despite low-to-moderate correlational results in one non-primary axis, the MetaMotionR IMUs performed well in tracking motion, and were able to estimate LDS with high accuracy using both SS and FE data ($0.807 \leq ICC_{2,1} \leq 0.919$). As such, MetaMotionR IMUs can be used for the clinical evaluation of spine movement quality during primary-axis (i.e., 1-dimensional rotation) movement tests (e.g., repetitive spine FE).

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Appendix A

Pilot Work

1. Problematic IMU orientation.

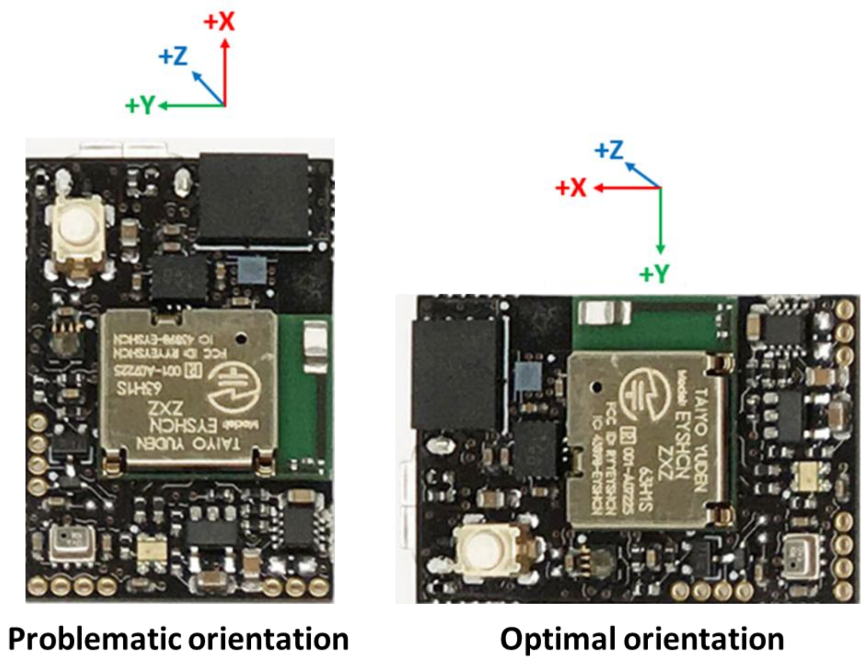


Figure A.1. *Problematic (left) and optimal (right) Mbientlab MetaMotionR inertial measurement unit (IMU) orientations.*

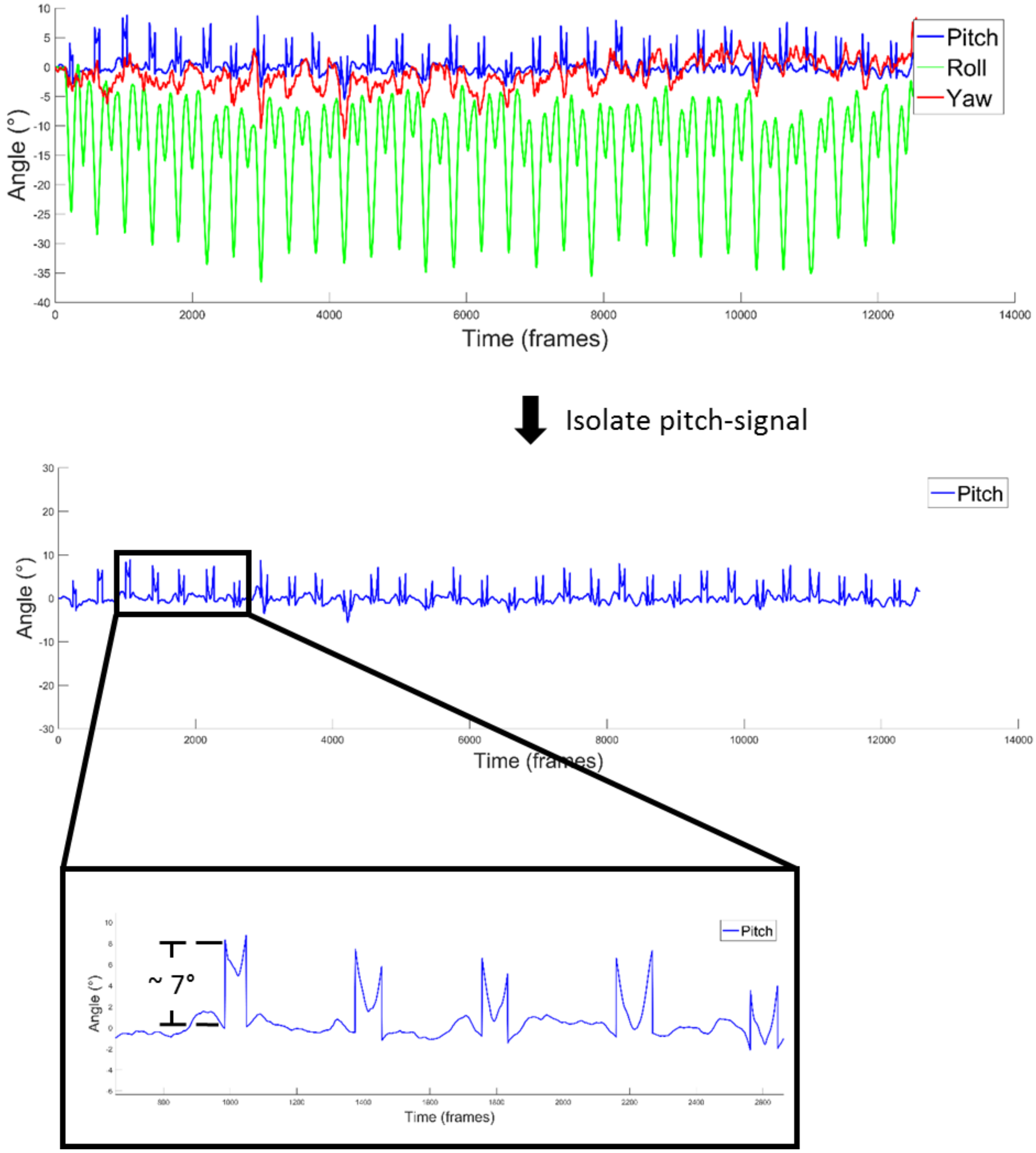


Figure A.2. *This image illustrates results from 35 cycles of repetitive spine flexion-extension (FE), in which the inertial measurement unit (IMU) was positioned in the problematic orientation (Figure A.1) and placed over the T_{10}-T_{12} spinous process. A zoomed in image of the pitch-signal reveals jumps in the data that are roughly 7° and very problematic for accurate motion tracking.*

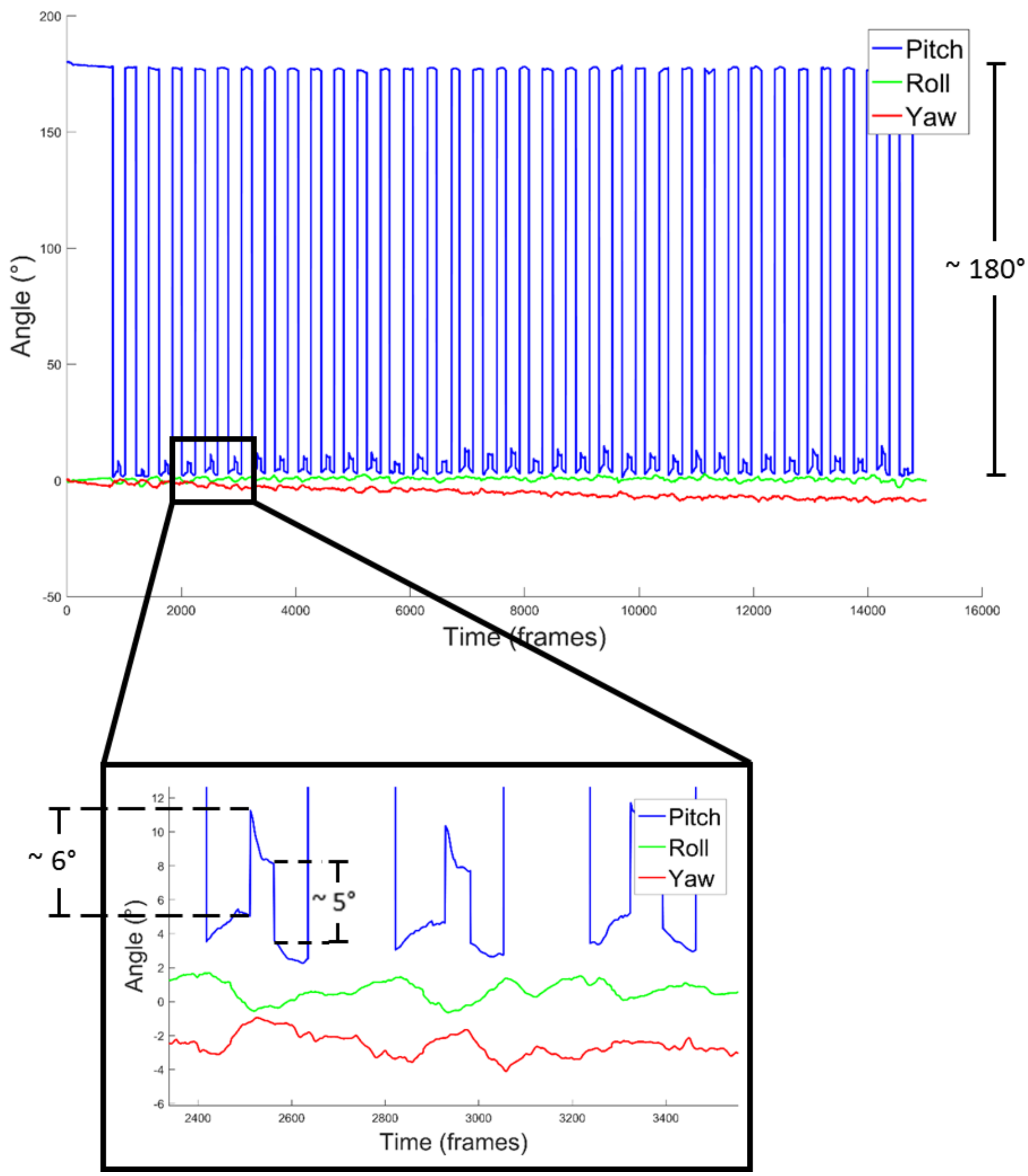


Figure A.3. *This image illustrates results from 35 cycles of repetitive spine flexion-extension (FE), in which the inertial measurement unit (IMU) was positioned in the problematic orientation (Figure A.1) and placed over the S_2 spinous process. A zoomed-in image of the pitch-signal shows jumps in the data that are roughly 180° or 5-6° in magnitude. Normally, the jumps from roughly 0°-180° and vice versa are easily rectified using a function that unwraps phase changes greater than pi or 2*pi; however, an error arises when the jumps are consistently lower than 180°, as this is requires additional corrective methods to obtain the "true" orientation, which leaves potential for additional error. It is possible that the reason for the discrepancy in phase changes is a slight offset in the internal (i.e., local) coordinate system in the MetaMotionR individual sensors (i.e., accelerometer, gyroscope, and magnetometer); as a result, calculation incongruences would exist when estimating Euler orientation in this orientation.*

2. Unpredictability when using the unwrap function.

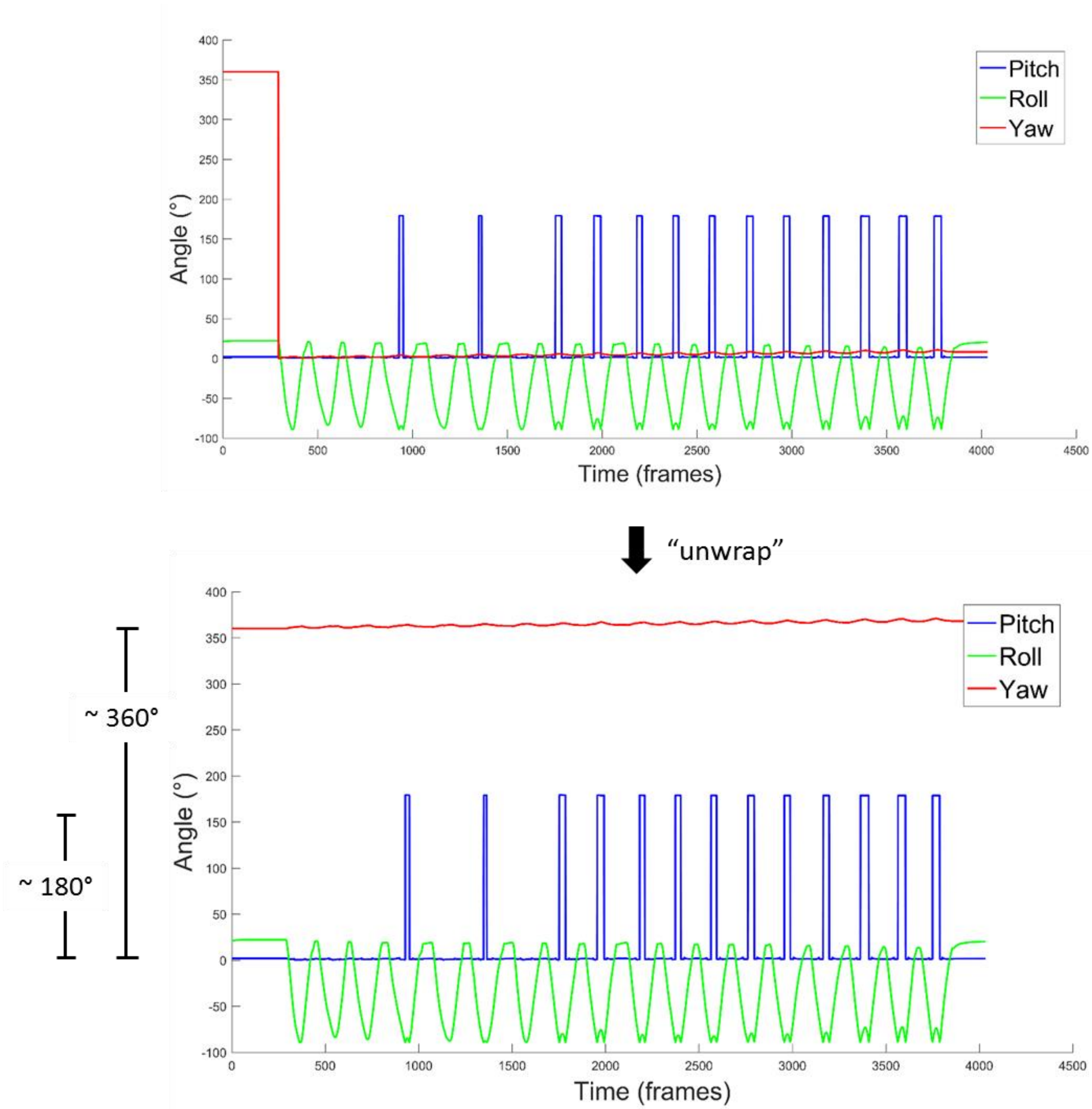


Figure A.4. *This image illustrates results from 18 cycles of repetitive rotational motion that simulates spine flexion-extension (FE), in which the inertial measurement unit (IMU) was positioned in the problematic orientation (Figure A.1). This data reveal jumps from roughly 0°-180° in the pitch-axis, and 0°-360° in the yaw-axis. After using the unwrap function (bottom), jumps in the pitch-signal still exist; however, the yaw-signal data hover somewhere around the 360° mark. The unwrap function was unpredictable with regards to where data would be centered (typically multiples of pi); as a result, data from both Mbientlab and Vicon had to be "zeroed" to standing in all axes (i.e., subtract all data from the first data point in each series) to account for this.*

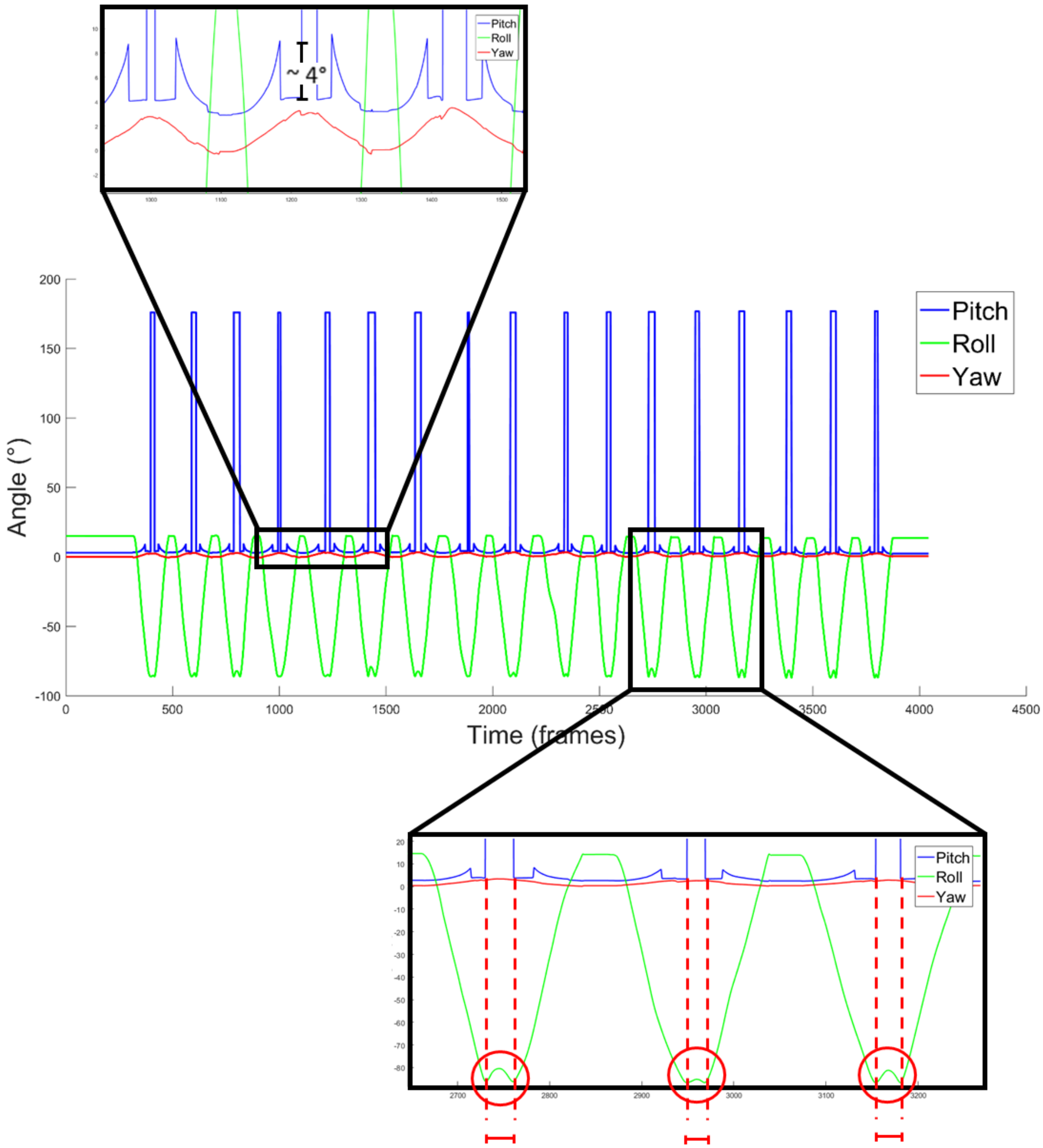


Figure A.5. *This image illustrates results from 17 cycles of repetitive rotational motion that simulates spine flexion-extension (FE), in which the inertial measurement unit (IMU) was positioned in the problematic orientation (Figure A.1). A zoomed-in image of the pitch-signal shows jumps in the data that are roughly 180° or 4° in magnitude (similar to Figure D.2). Coincidentally, the 180° jumps in the pitch-signal line up with what appear to be inversions in the roll-signal when the angle reaches -90°. This likely has something to do with offset internal axes and calculation incongruences in this orientation.*

3. Gimbal lock.

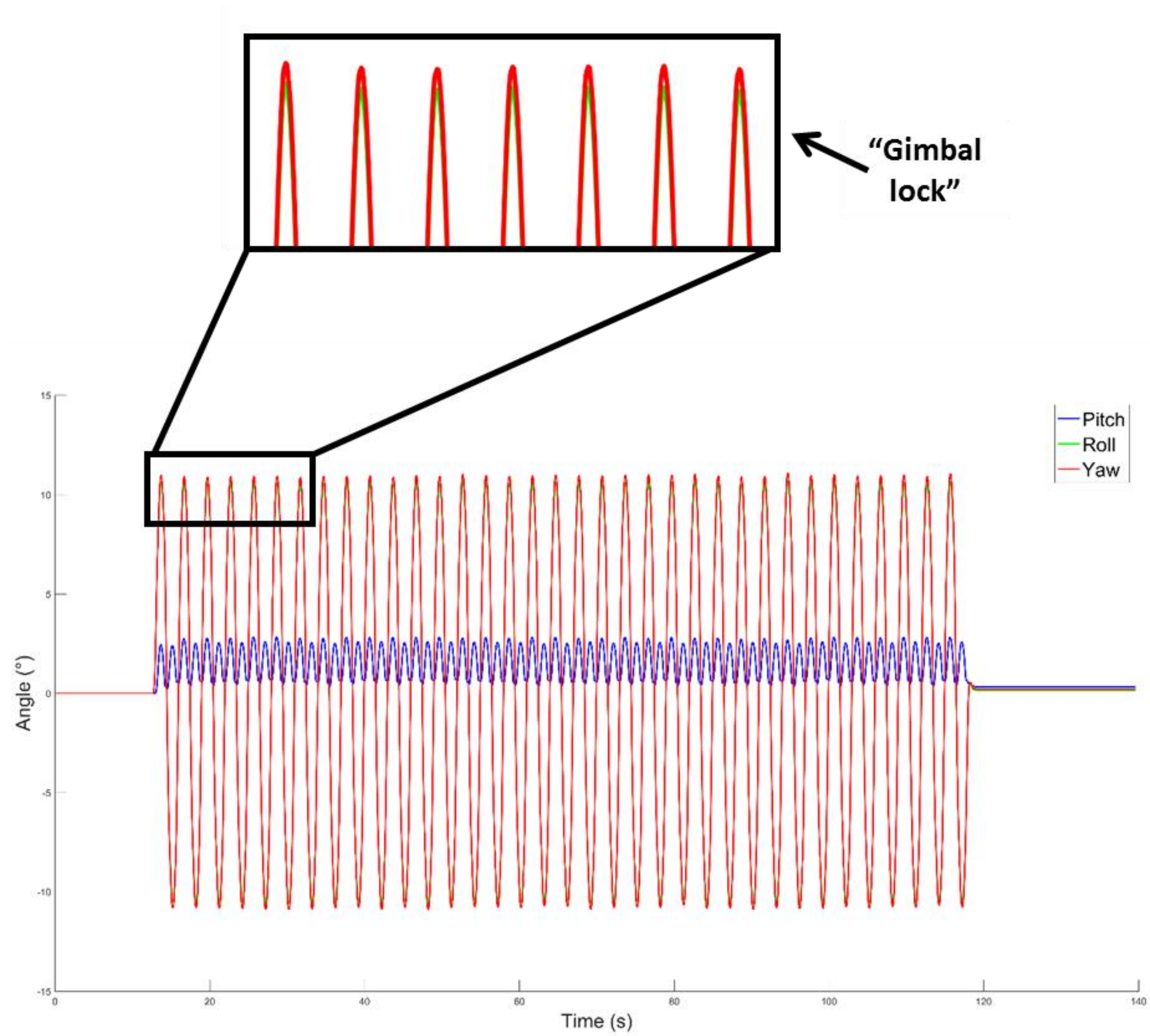


Figure A.6. *This image represents results from 35 cycles of repetitive rotational motion that simulated spine flexion-extension (FE), in which the inertial measurement unit (IMU) was positioned in the problematic orientation (Figure A.1). In this test, the IMU experienced gimbal lock, in which the roll- and yaw-axes became "locked", essentially eliminating 1 degree-of-freedom, and consequently data from one axis of rotation.*

4. Gyroscopic drift.

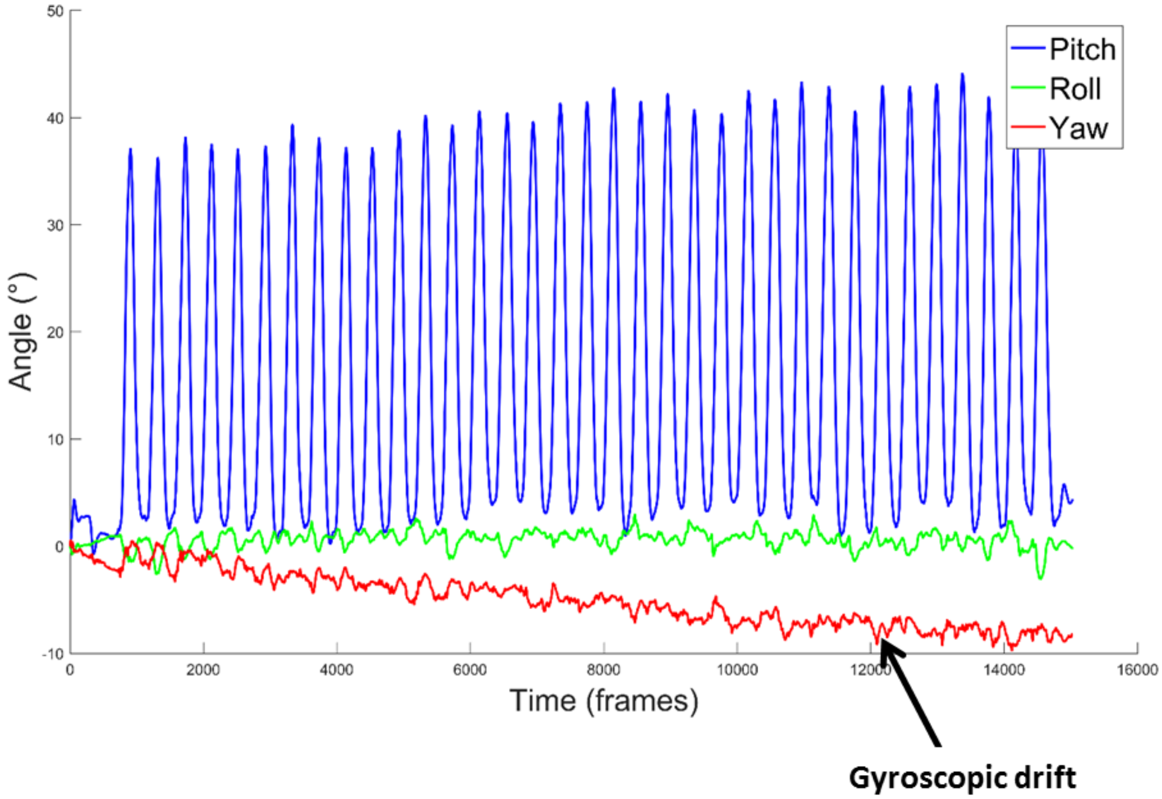


Figure A.7. *This image illustrates results from 35 cycles of repetitive flexion-extension (FE), where the inertial measurement unit (IMU) was placed over the T_{10}-T_{12} spinous process in the orientation used in Chapters 4 and 5 (i.e., the optimal orientation; Figure A.1). The yaw-signal experiences gyroscopic drift throughout the entire duration of the movement. The on-board sensor fusion utilized by Mbientlab Inc. should account for and correct this; however, this is not the case. In Chapters 4 and 5, a linear line of best-fit was subtracted from the yaw-signal; however, it is not certain whether gyroscopic drift behaves this way, leaving room for error to be introduced.*

5. **Inconsistent sampling rate – streaming vs. logging.**

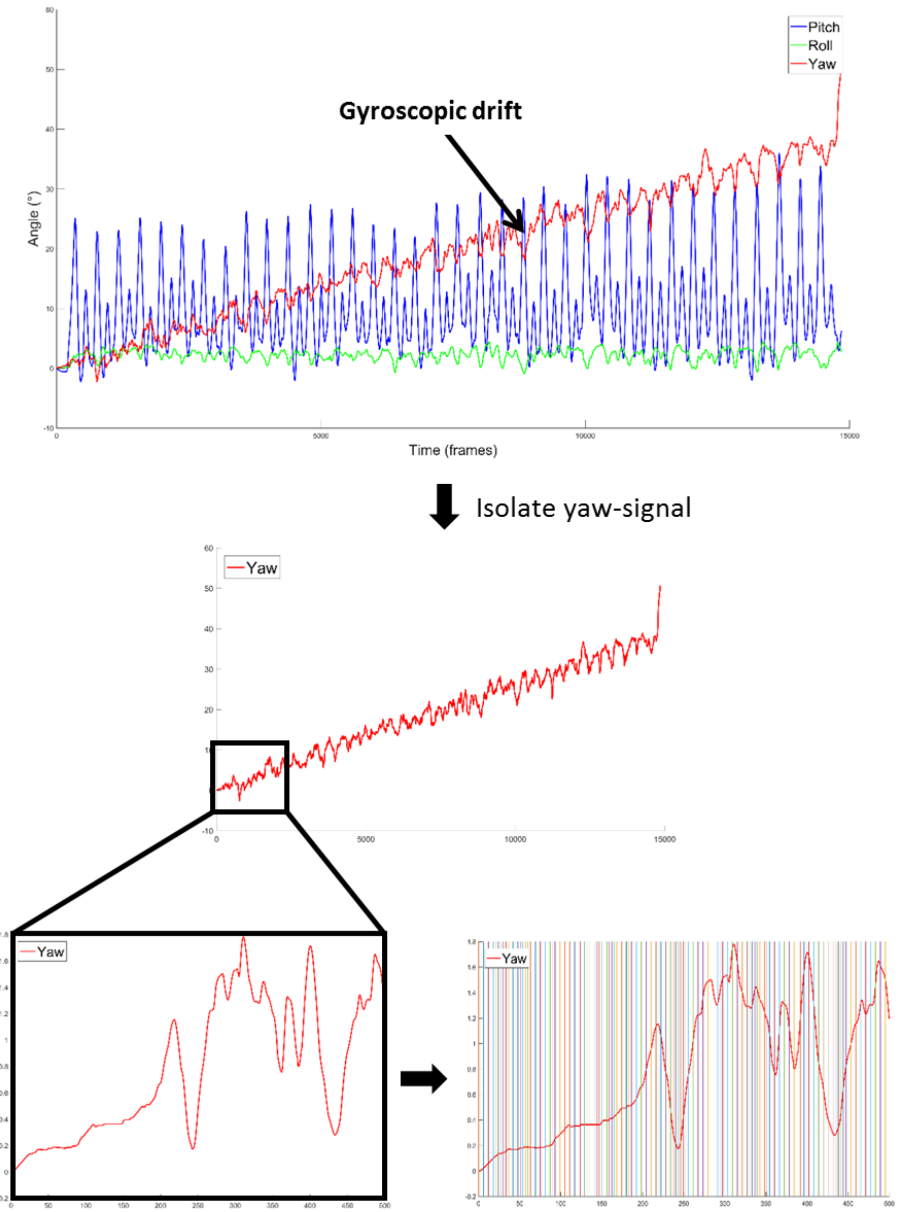
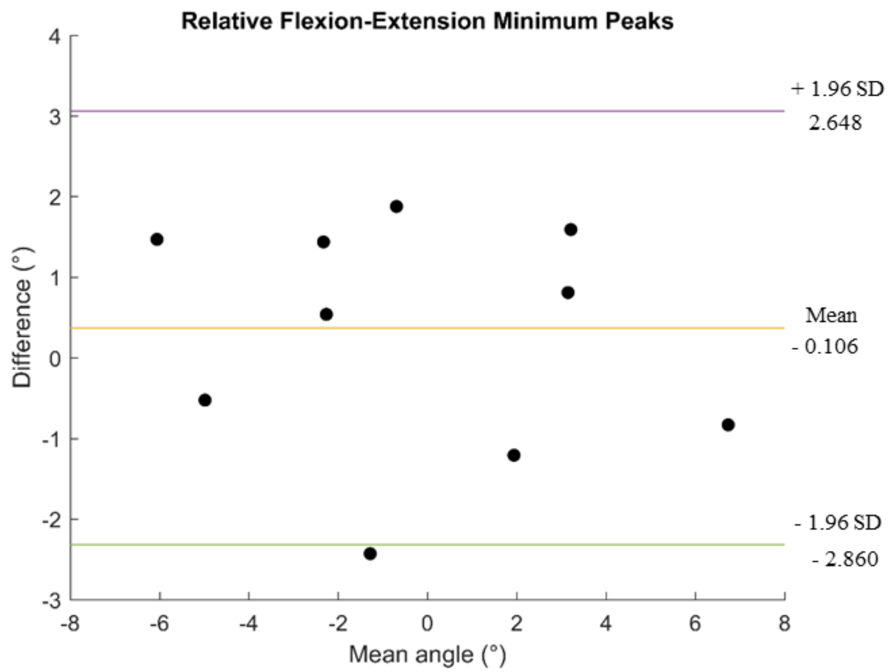


Figure A.8. *This image illustrates results from 35 cycles of repetitive flexion-extension (FE), where the inertial measurement unit (IMU) was placed over the* T_{10}*-*T_{12} *spinous process in the orientation used in Chapters 4 and 5 (i.e., the optimal orientation; Figure A.1). In this trial, data were streamed via Bluetooth low energy (BLE). The bottom left image is a zoomed-in picture of the yaw-signal (which also experiences gyroscopic drift). Vertical lines were plotted on the x-axis (which represents the framerate at which data were streamed); when data were streamed, the frequency at which the data were captured was inconsistent, which is very troublesome especially when assessing performance relative to gold-standard optical motion capture. This issue did not occur when data were logged onto the sensors, and downloaded after each trial was completed; however, logging is not ideal for providing real-time feedback in clinical situations.*

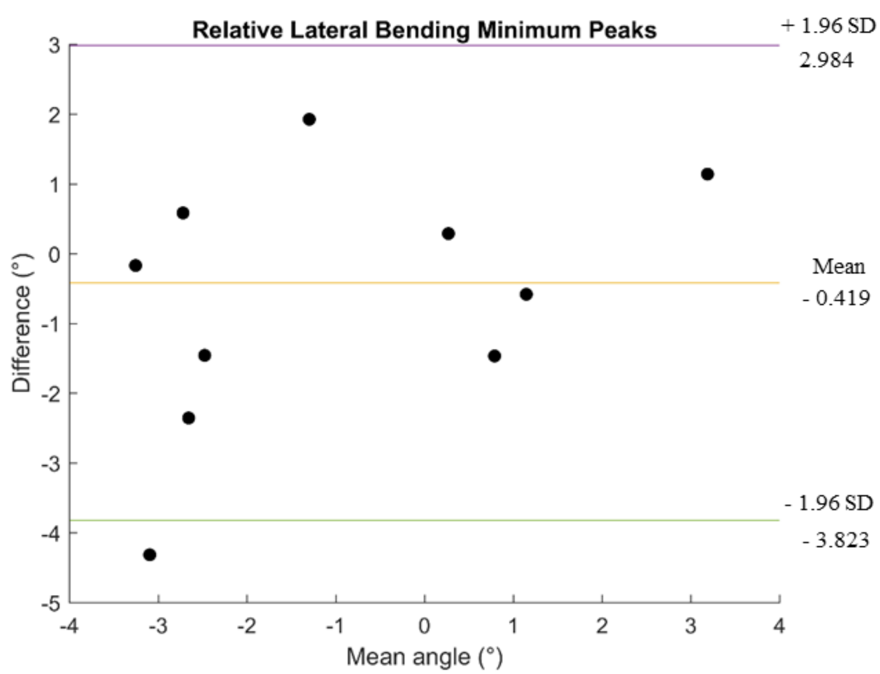
Appendix B

Bland-Altman Analysis

(a)



(b)



(c)

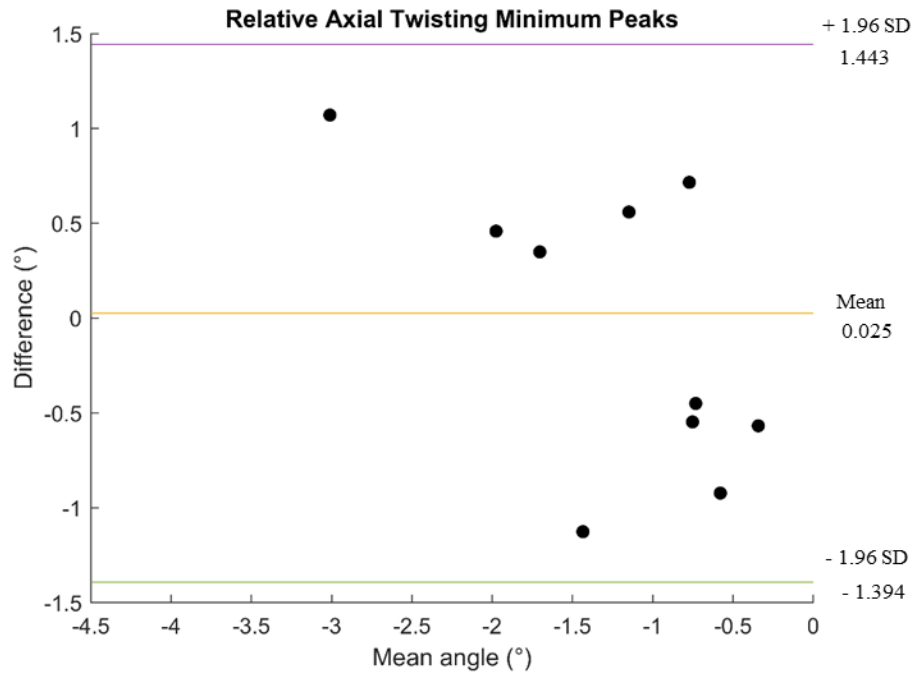
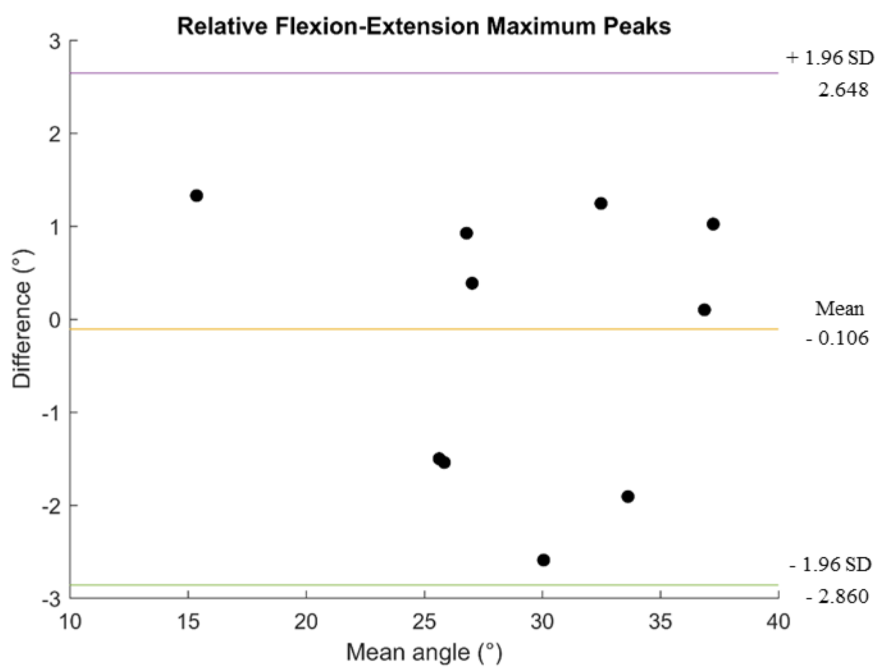
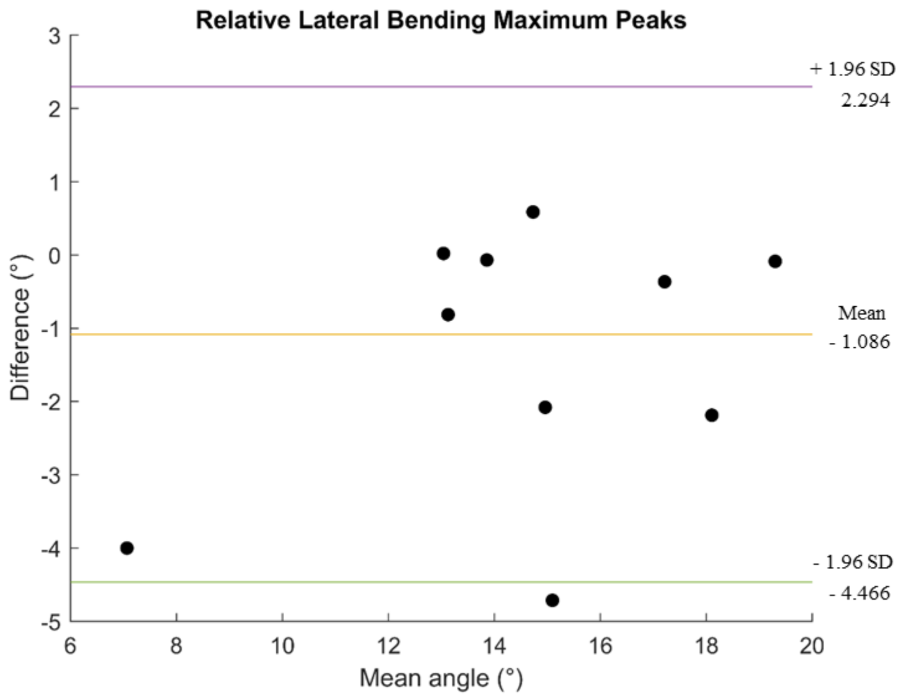


Figure B.1. *Bland-Altman plot for relative cycle-to-cycle minimum values between T_{10}-T_{12} and S_2 inertial measurement units (IMUs)/rigid-body marker clusters (Chapter 5). (a) Flexion-extension (FE); (b) Lateral bending (LB); (c) Axial twisting (AT).*

(a)



(b)



(c)

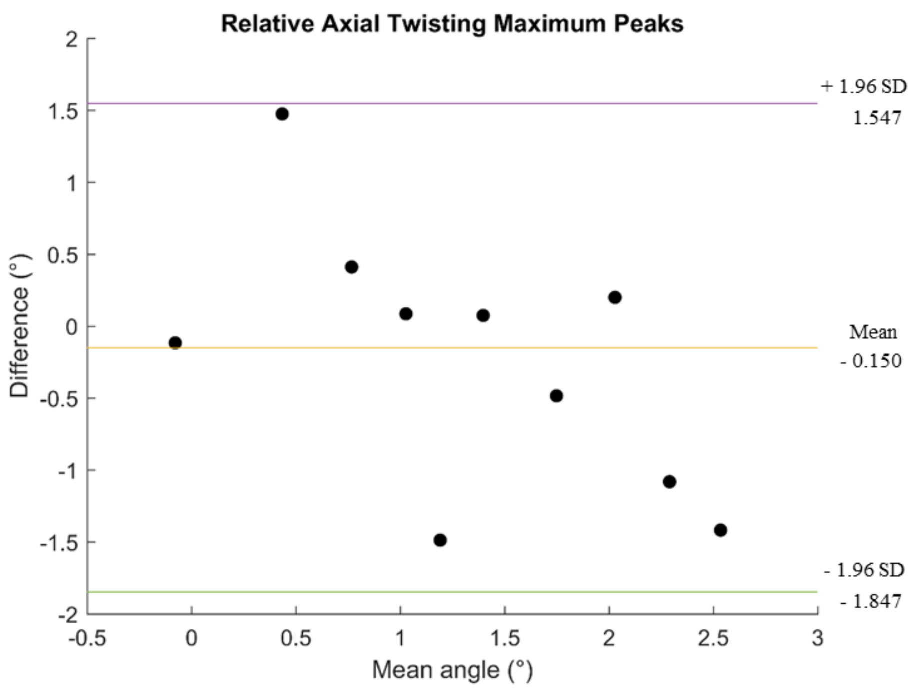


Figure B.2. *Bland-Altman plot for relative cycle-to-cycle maximum values between T_{10}-T_{12} and S_2 inertial measurement units (IMUs)/rigid-body marker clusters (Chapter 5). (a) Flexion-extension (FE); (b) Lateral bending (LB); (c) Axial twisting (AT).*

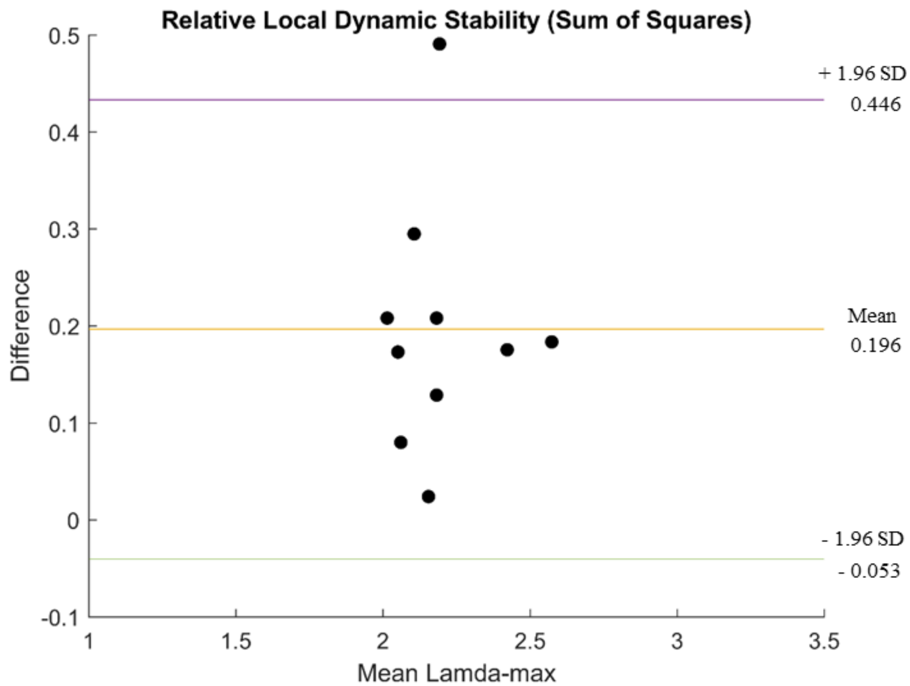


Figure B.3. *Bland-Altman plot for local dynamic stability (LDS; λmax) values when using the sum of squares (SS) of relative angles (T_{10}-T_{12} with respect to S_2; Chapter 5).*

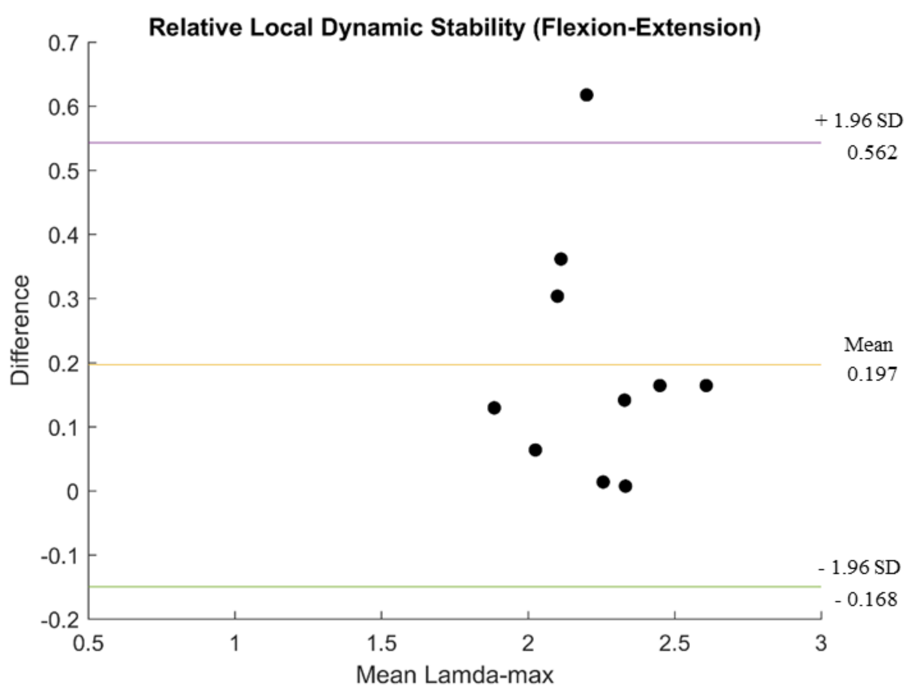


Figure B.4. *Bland-Altman plot for local dynamic stability (LDS; λ_{max}) values when using the flexion-extension (FE) data of relative angles (T_{10}-T_{12} with respect to S_2; Chapter 5).*

Appendix C

Mbientlab MetaMotionR Product Specification

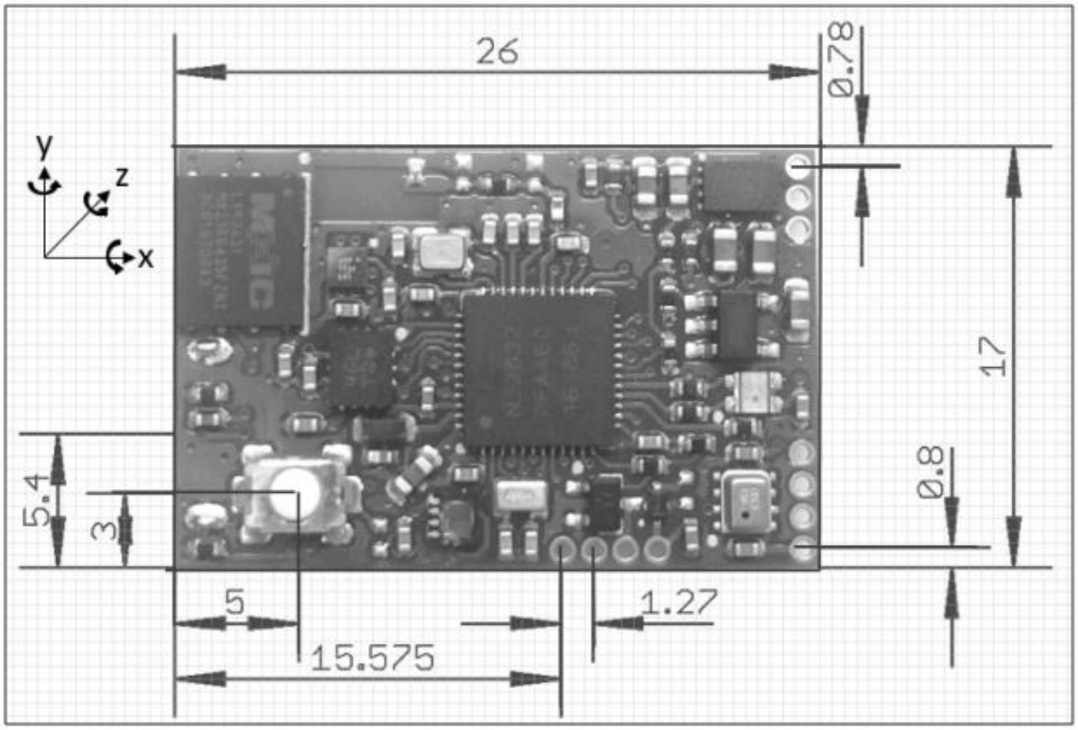


Figure C.1. *Mechanical specifications for Mbientlab MetaMotionR inertial measurement units (IMUs).*

Spec	Description	Min.	Typ.	Max.	Units
	Measurement range.	±2		±16	g
	Resolution.	2048		16384	counts/g
f_{DATA}	Data sample frequency.	0.78		1600	Hz
$I_{12.5}$	Low data rate current (3.125 Hz).		5		uA
I_{100}	Mid data rate current (100 Hz).		24		uA
I_{1600}	High data rate current (1600 Hz).		180	300	uA
$I_{STANDBY}$	Standby current.		3	10	uA

Figure C.2. *Accelerometer specifications for Mbientlab MetaMotionR inertial measurement units (IMUs).*

Spec	Description	Min.	Typ.	Max.	Units
	Measurement range.	±125		±2000	°/s
	Resolution.	16		262	counts/°
f_{DATA}	Data sample frequency.	25		3200	Hz
I_{GYRO}	Gyro active current. All Data Rates.		850	900	uA
$I_{STANDBY}$	Standby current. Included in Accel Standby Current.				

Figure C.3. *Gyroscope specifications for Mbientlab MetaMotionR inertial measurement units (IMUs).*

Spec	Description	Min.	Typ.	Max.	Units
	Measurement range.	±1200	±1300		uT
	Heading Accuracy.			±2.5	°
f_{DATA}	Data rate.		25	300	Hz
$I_{STANDBY}$	Standby current.		1	3	uA

Figure C.4. *Magnetometer specifications for Mbientlab MetaMotionR inertial measurement units (IMUs).*

Appendix D

Ethics Approval – Study 2

File Number: H08-17-26 **Date (mm/dd/yyyy):** 11/08/2017

Université d'Ottawa University of Ottawa
Bureau d'éthique et d'intégrité de la recherche Office of Research Ethics and Integrity

Ethics Approval Notice

Health Sciences and Science REB

Principal Investigator / Supervisor / Co-investigator(s) / Student(s)

First Name	Last Name	Affiliation	Role
Ryan	Graham	Health Sciences / Human Kinetics	Principal Investigator
Kristen	Beange	Health Sciences / Human Kinetics	Research Assistant

File Number: H08-17-26

Type of Project: Professor

Title: Validation of a wearable sensor mobile application for the investigation of spine movement quality

Approval Date (mm/dd/yyyy)	Expiry Date (mm/dd/yyyy)	Approval Type
11/08/2017	11/07/2018	Approval

Special Conditions / Comments:
N/A

550, rue Cumberland, pièce 154 550 Cumberland Street, room 154
Ottawa (Ontario) K1N 6N5 Canada Ottawa, Ontario K1N 6N5 Canada
(613) 562-5387 • Téléc./Fax (613) 562-5338
www.recherche.uottawa.ca/deontologie/ www.research.uottawa.ca/ethics/

Appendix E

English Consent Form – Study 2

uOttawa

Université d'Ottawa
Faculté des sciences
de la santé

École des sciences de
l'activité physique

University of Ottawa
Faculty of Health
Sciences

School of Human Kinetics

Research Consent Form

Research Project Title:

Validation of wearable sensor mobile application for the evaluation of spine movement quality

Principal Investigator and Research Assistant:

Dr. Ryan Graham
Kristen Beange
University of Ottawa
Faculty of Health Sciences
Department of Human Kinetics

Background and Purpose of the Study:
Despite the vast population of low back pain sufferers, accurate diagnosis and treatment of the disorder is insufficient. There is currently a lack of understanding regarding the various mechanisms that drive the disorder, resulting in inappropriate treatment. It is documented that people with low back pain move differently based on the dominant factor driving the disorder. The ability for health care providers to objectively measure spinal movement quality in clinics will greatly improve diagnostic procedures and spine care. Our lab has developed and is refining a framework for performing wearable-based spine movement quality analyses in clinical settings using a custom mobile application and cloud computing; however, prior to implementing the framework on a large scale it is necessary to assess and validate the performance of selected sensors for orientation tracking and measurement of spine movement quality variables. Therefore, the goal of this research is to validate wearable inertial measurement unit (IMU) sensor performance and placement for the evaluation of spine movement quality relative to gold-standard motion capture equipment. To validate the IMU instruments' ability to capture spine movement quality in a group of healthy participants, local dynamic stability, coordination, variability, and judder will be compared between motion capture systems.

Description of Study Procedures:
You are invited to participate in a one-day motion analysis procedure for approximately 1 hour at the University of Ottawa Human Movement Biomechanics Laboratory (200 Lees Avenue, E020). The study procedure will involve the validation of wearable sensor and video-based depth sensor data to that of standard motion capture equipment for the evaluation of spine movement quality.

www.uOttawa.ca

Before the procedure, you will be asked to change into form fitting spandex clothing for the remainder of the data collection. Reflective markers and wearable motion sensors will be attached to the lower back and pelvis with tape around your trunk, and waist.

The movement protocol will involve 4 trials of 35 cycles of repetitive trunk movement in various directions (i.e., trunk flexion-extension, lateral bending, axial twist, and complex movement). All trials will be rate-controlled. During the repetitive trunk movement tasks, you will be asked to touch two targets with your hands that represent end range of motion in each direction. You will be given a 5-minute rest between tasks to prevent fatigue, and will be allowed to practice tasks to ensure you are comfortable and understand the instructions. More time will be provided if it is required to ensure no signs of fatigue are present. You will not be constrained in any way during the duration of the movement protocol, as the goal of the study is to measure natural kinematic behaviour and coordination.

Possible Risks and Discomforts:
There are no significant risks associated with participating in this study. You may experience pain and fatigue due to the nature of the movement protocol. However, sufficient rest will be given to reduce these effects. Should you experience any major discomfort, please tell us immediately and seek primary care from a medical professional on campus (100 Marie Curie, Ottawa, Tel.: 613-564-3950) or a medical professional of your choosing.

Possible Benefits:
You will not directly benefit from participating in this study. However, the results of this study will help advance the evaluation of spine movement quality in clinical settings.

Voluntary Participation:
You are not obliged to participate in this study; participation in this study is voluntary. You may also withdraw from the study at any time with no penalty or coercion.

Confidentiality:
All personal information is kept confidential unless release is required by law. Information gained from this study will be stored electronically and will need a password to access. Paper study records are stored in a locked cabinet and will be destroyed after 5 years; electronic records will be deleted and paper records will be shredded. You will not be identified by name in any reports of the completed study. Your anonymity will be strictly maintained – you will not be identified by your name, but will be determined by an independent study number.

Compensation:
No monetary compensation will be provided for participation in this study. However the data will provide significant contributions to validating the wearable IMU sensors and Microsoft Kinect for evaluation of spine movement quality.

Exclusion Criteria:
You will be excluded from the study if you have any history of the following: cardiovascular conditions, neurologic disorders (neuropathy, neurodegenerative conditions), specific LBP (discogenic, mechanical, myofascial), use of medication (anti-inflammatories, analgesics,

anticonvulsants, antidepressants), history of low back injury (discogenic mechanical) use of anticoagulant therapy, stroke or TIA, spine trauma, motor vehicle accident, lumbar spine surgery, hypertension, CTD and focal neurological symptoms (sensory/motor).

Questions about the Study:
You are free to ask questions at any time; you can contact the principal investigators by email: Kristen Beange and/or Dr. Ryan Graham. This project is funded by the Natural Sciences and Engineering Research Council of Canada. The University of Ottawa research ethics board has approved all ethical aspects of this research project. If you have any questions regarding the ethical conduct of this study, you may contact the Protocol Officer for Ethics in Research, University of Ottawa, Tabaret Hall, 550 Cumberland Street, Room 154, Ottawa ON, K1N 6N5. Tel.: (613) 562-5387 Email: ethics@uottawa.ca

Research Project Title: Validation of wearable sensor and video-based depth sensor for the evaluation of spine movement quality

Consent:
I have read this consent form, and I agree to participate in the procedures of this study.

____
Printed Name of Participant

______________________________ ______________________________
Signature of Participant Date

Investigator Statement (or Person Explaining the Consent):
I have carefully explained to the research participant the nature of the above research study. To the best of my knowledge, the research participant signing this consent form understands the nature, demands, risks and benefits involved in participating in this study. I acknowledge my responsibility for the care and well-being of the above research participant, to respect the rights and wishes of the research participant, and to conduct the study according to applicable Good Clinical Practice guidelines and regulations.

____
Name of Investigator/Delegate (printed)

______________________________ ______________________________
Signature of Investigator/Delegate Date

Informed Consent to have Pictures Taken:
I consent to have side view pictures taken of myself completing the experiment and understand that no pictures will be taken at any point without me knowing. I also understand that if any of these pictures are used in a subsequent presentation or publication, that my face and any other identifiers will be blurred. You can still participate in the research study without consenting to have pictures taken.

______________________________ ______________________________
Name Date

____
Signature

______________________________ ______________________________
Witness Name Witness Signature

Future Participation:

- ☐ I am interested in being contacted to participate in future research performed by this laboratory (your email information will be saved in a password protected file).

Appendix F

French Consent Form – Study 2

Université d'Ottawa
Faculté des sciences de la santé

École des sciences de l'activité physique

University of Ottawa
Faculty of Health Sciences

School of Human Kinetics

www.uOttawa.ca

Formulaire de consentement à la recherche

Titre du projet de recherche: Validation de la performance de capteur portable et le capteur de profondeur basé sur la vidéo pour l'évaluation de la qualité du mouvement de la colonne vertébrale

Chercheurs principaux et assistant de recherche:

Kristen Beange
Dr. Ryan Graham
University of Ottawa
Faculty of Health Sciences
Department of Human Kinetics

Contexte et objectif de l'étude:
Malgré la vaste population de personnes souffrant de douleurs lombaires, la précision du diagnostic et du traitement de la maladie est insuffisante. Il existe un manque de compréhension concernant les différents mécanismes qui entraînent le trouble, ce qui entraîne un traitement inapproprié. Il est documenté que les personnes souffrant de lombalgie se déplacent différemment en fonction du facteur dominant responsable du trouble. La capacité des fournisseurs de soins de santé à mesurer objectivement la qualité du mouvement de la colonne vertébrale dans les cliniques améliorera grandement les procédures de diagnostic et les soins de la colonne vertébrale. Notre laboratoire a développé et raffine un système permettant d'effectuer des analyses sur la qualité du mouvement de la colonne vertébrale dans des environnements cliniques en utilisant une application mobile personnalisée et le cloud computing; cependant, avant de mettre en œuvre le système à grande échelle, il est nécessaire d'évaluer et de valider les performances des capteurs sélectionnés pour l'alignement de l'orientation et la mesure des variables de qualité du mouvement de la colonne vertébrale. Par conséquent, le but de cette recherche est de valider la performance et le positionnement de centrale inertielle portable pour l'évaluation de la qualité du mouvement de la colonne vertébrale par rapport à l'équipement de capture de mouvement standard. Pour valider la capacité des centrales inertielle de capturer la qualité du mouvement de la colonne vertébrale dans un groupe de participants en santé, la stabilité dynamique locale, la coordination, la variabilité et le cahot seront comparés entre les systèmes de capture de mouvement.

Description des procédures de l'étude:
Vous êtes invités à participer à une un-jour analyse de mouvement procédure pour approximativement 1 heure au Laboratoire de biomécanique des mouvements humains de l'Université d'Ottawa (200, avenue Lees, E020). L'étude impliquera la validation des données de capteur portable à celle et capteur de profondeur basé sur la vidéo de l'équipement de capture de mouvement standard pour l'évaluation de la qualité du mouvement de la colonne vertébrale.

Avant la procédure, nous vous demanderons de porter des vêtements spandex pour le reste de la collecte de données. Des marqueurs réfléchissants et des détecteurs de mouvement portables seront attachés au bas du dos, et au bassin avec du ruban adhésif autour du tronc et de la taille.

Le protocole de mouvement comprendra 4 essais de 35 cycles de répétitive mouvement du tronc dans diverses directions (i.e., flexion/extension, flexion latérale, torsion axiale, et mouvement complexe). Tous les essais sera à taux contrôlé. Au cours de les tâches répétitives de mouvement du tronc, on vous demandera de toucher deux cibles avec vos mains qui représentent la fin de la gamme de mouvement dans chaque direction. Vous aurez un repos de 5 minutes entre les tâches pour éviter la fatigue, et serez autorisé de pratiquer les tâches pour vous assurer que vous êtes à l'aise et comprenez les instructions. Plus de temps sera fourni s'il est nécessaire pour s'assurer qu'il n'aura aucun signe de fatigue. Vous ne serez soumis à aucune contrainte pendant la durée du protocole de mouvement, car le but de l'étude est de mesurer le comportement cinématique naturel et la coordination.

Risques et inconforts possibles:
Il n'y a aucun risque significatif associé avec la participation à cette étude. Il est possible de ressentir de la douleur et de la fatigue en raison de nature de la tâche de flexion. Cependant, un repos suffisant sera fourni pour réduire ces effets. Si vous ressentez un inconfort majeur, veuillez nous le signaler immédiatement et demander les soins primaires d'un professionnel de la santé sur le campus (100 Marie Curie, Ottawa, Tél.: 613-564-3950) ou un professionnel médical de votre choix.

Avantages possibles:
Vous ne bénéficierez pas directement de la participation à cette étude. Cependant, les résultats de cette étude aideront à progresser l'évaluation de la qualité du mouvement de la colonne vertébrale dans les milieux cliniques.

Participation volontaire :
Vous n'êtes pas obligé de participer à cette étude. La participation à cette étude est volontaire. Vous pouvez également vous retirer de l'étude à tout moment sans pénalité.

Confidentialité:
Tous les renseignements personnels sont gardés confidentiels à moins que la libération ne soit requise par la loi. Les renseignements tirés de cette étude seront enregistrés électroniquement et auront besoin d'un mot de passe pour y accéder. Les dossiers d'études sur papier sont entreposés dans un cabinet verrouillé et seront détruits après 5 ans. Aussi, les dossiers électroniques seront supprimés et les documents papier seront détruits. Vous ne serez pas identifié par nom dans les

rapports finaux de l'étude. Votre anonymat sera strictement maintenu - vous ne serez pas identifié par votre nom, mais sera déterminé par un numéro d'étude.

Compensation:
Aucune compensation monétaire ne sera accordée pour participer à cette étude. Cependant, les données fourniront d'importantes contributions pour valider les capteurs portables de centrale inertielle et Microsoft Kinect pour l'évaluation de la qualité du mouvement de la colonne vertébrale.

Critère d'exclusion:
Tous les participants: Vous serez exclu de la participation à cette étude si vous avez déjà vécu: des troubles cardiovasculaires, des troubles neurologiques (neuropathie, maladies neurodégénératives), des douleurs lombaires (discogène, mécanique, myofasciale), une blessure à la cheville (foulée, fracturée) l'utilisation de médicaments (anti-inflammatoires, antidépresseurs), antécédents de lésions lombaires (mécanique discogène) utilisation d'une thérapie anticoagulante, AVC ou AIT, traumatisme de la colonne vertébrale, accident de véhicule, chirurgie de la colonne lombaire, hypertension, CTD et symptômes neurologiques focaux (sensoriels / moteurs).

Participants sains: Vous serez exclu de la participation à cette étude si vous avez des antécédents de lombalgie.

Questions sur l'étude:
Vous êtes bienvenue de poser des questions à tout moment; Vous pouvez communiquer avec les chercheurs principaux par courriel: Kristen Beange et/ou Dr. Ryan Graham. Ce projet est financé par le Conseil de recherches en sciences naturelles et en génie du Canada. Le Conseil d'éthique de la recherche de l'Université d'Ottawa a approuvé tous les aspects éthiques de ce projet de recherche. Si vous avez des questions sur la conduite éthique de cette étude, vous pouvez communiquer avec l'agent de protocole pour l'éthique en recherche, Université d'Ottawa, Hall Tabaret, 550, rue Cumberland, pièce 154, Ottawa ON, K1N 6N5. Tél.: (613) 562-5387 Courriel: ethics@uottawa.ca

Titre du projet de recherche: **Validation de la performance de capteur portable et le capteur de profondeur basé sur la vidéo pour l'évaluation de la qualité du mouvement de la colonne vertébrale**

Consentement:
J'ai lu ce formulaire de consentement et j'accepte de participer aux procédures de cette étude.

____
Nom imprimé du participant

____________________________________ ______________________________
Signature du participant Date

Déclaration de l'enquêteur:
J'ai soigneusement expliqué au participant de la recherche la nature de l'étude de recherche ci-dessus. À ma connaissance, le participant à la recherche signant ce formulaire comprend la nature, les exigences, les risques et les avantages associés à la participation à cette étude. Je reconnais ma responsabilité pour la sécurité et le bien-être du participant à la recherche susmentionné, de respecter les droits et les besoins du participant à la recherche et de mener l'étude conformément aux lignes directrices et aux règlements applicables en matière de bonnes pratiques cliniques.

____
Nom de l'enquêteur / délégué

____________________________________ ______________________________
Signature de l’enqueteur/Delegue Date

Consentement à prendre des photos:
Je consens à avoir des photos de vue latérale de moi-même complétant l'expérience, et comprends que les photos ne seront prises à aucun moment sans me savoir. Je comprends également que si l'une de ces images est utilisée dans une présentation ou une publication ultérieure, mon visage et tout autre identifiant seront flous. Vous pouvez toujours participer à l'étude sans consentir à prendre des photos.

______________________________ ______________________________
Nom Date

____
Signature

______________________________ ______________________________
Nom du témoin Signature du témoin

Participation future:
Je suis intéressé à être contacté pour participer à de recherches futures effectuées par ce laboratoire (vos informations de courriel seront enregistrées dans un fichier protégé par mot de passe).