ASSESSING MUSCLE FATIGUE USING ELECTROMYOGRAPHY COMPLEXITY AND WAVELET METHODS DURING REPETITIVE TRUNK MOVEMENTS

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List of Acronyms

ANOVA	Analysis of Variance
BPM	Beats Per Minute
CV	Conduction Velocity
CWT	Continuous Wavelet Transform
DC	Direct Current
DFA	Detrended Fluctuation Analysis
EMG	Electromyography
F-E	Flexion-Extension
L3	The Third Lumbar Spine Vertebra
LES	Lumbar Erector Spinae
MFC	Major Frequency Components
MMF	Myoelectric Manifestations of Fatigue
MSD	Musculoskeletal Disorders
MSE	Modified Sample Entropy
MUAP	Motor Unit Action Potential
MVC	Maximum Voluntary Contraction
PAR-Q+	Physical Activity Readiness Questionnaire for Everyone
SampEn	Sample Entropy
sEMG	Surface Electromyography
SD	Standard Deviation
SMCI	Spine Motion Composite Index
STFT	Short-Time Fourier Transform
T8	The Eighth Thoracic Spine Vertebra
VAS	Visual Analogue Scale
WSIB	Workplace Safety and Insurance Board of Ontario
WT	Wavelet Transform

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ABSTRACT

Prolonged performance of repetitive movements can lead to muscle fatigue, negatively impacting human performance. As a result, researchers have explored methods to effectively assess and quantify this phenomenon, where surface electromyography (sEMG) is a popular method to reveal information regarding muscle contractions. The continuous wavelet transform (CWT) captures the instantaneous frequency components of signals, which make it suitable for sEMG analyses of dynamic muscle contractions. Moreover, sample entropy (SampEn) can be used to quantify the complexity of the sEMG signal, which provides novel insights for assessing muscle fatigue. However, the amount of research on sEMG complexity analyses to assess muscle fatigue during dynamic contractions is limited. Therefore, the goal of this work was to: 1) calculate and compare the major frequency components (MFC) from CWT and modified SampEn (MSE) of sEMG signals during a repetitive trunk flexion-extension (F-E) task; and 2) determine which sEMG metric is more closely related to ground truth fatigue indicators including the visual analogue scale (VAS), maximum pulling force, and kinematic variability of movements.

Seven male and five female participants performed up to twelve sets of 50 repetitive trunk FE movements based on pre-defined stopping criteria. Their VAS and maximum pulling strength were measured immediately after each set. The MFC from CWT and the MSE values were calculated from both the left and the right lumbar erector spinae (LES) throughout the movements. Trunk dynamic kinematic variability of every set was quantified by the spine motion composite index (SMCI). Repeated measures correlation coefficients (r) were used to calculate the relationship between MFC and MSE, as well as between these outcome variables and VAS, maximum pulling force, and SMCI across all participants.

Visual inspection revealed that on average that both the MFC and the MSE of sEMG signals decreased as the fatiguing protocol progressed, where a significant correlation was

found between the two sEMG metrics (r = 0.270, p = 0.006). No significant correlations were found between the two sEMG measures and the maximum pulling strength (r_{MFC} = 0.101, p = 0.313; r_{MSE} = 0.193, p = 0.051). Nevertheless, both sEMG metrics showed significant correlations with fatigue VAS, with the MFC having stronger correlations across all the participants (r_{MFC} = −0.602, p < 0.001) than the MSE (r_{MSE} = −0.248, p = 0.011). Significant negative correlations were also observed between the SMCI and both sEMG MFC (r_{MFC} = −0.268, p = 0.010) and MSE (r_{MSE} = −0.335, p = 0.001).

Both sEMG metrics mapped onto the perceived fatigue and movement pattern variations during the task, suggesting they could be used for assessing fatigue during dynamic movements. However, the MFC had a stronger correlation with participants' perceived fatigue whereas MSE was more strongly correlated with kinematic variability. Continued research is required to further examine these relationships, as well as determine the best method of assessing changes in force output with muscle fatigue.

CHAPTER 1: INTRODUCTION

1.1 Background

Prolonged performance of repetitive movements can lead to a decrease in muscle force or power generation (Edwards, 1981; Vøllestad, 1997). This phenomenon, also known as muscle fatigue, may cause changes in motor control (Gandevia, 2001) and movement behaviour (Monjo et al., 2015), which could increase the risk of work-related accidents such as strains and fractures (Kajimoto, 2008; Kumar, 2001; Yung and Wells, 2016) and induce musculoskeletal disorders (Antwi-Afari et al., 2017; Everett, 1999; Nussbaum, 2001; Radwin et al., 2001; Tang, 2022). According to the Workplace Safety and Insurance Board of Ontario (WSIB), sprains and strains were the leading sources of injuries in the workplace across all industry types in Ontario from 2005 to 2019, with the low back being the most injured body part (WSIB, 2022). Although muscle fatigue was not used in their documents it could be an important factor affecting the incidence rate. However, the term *muscle fatigue* does not have a universal definition (Barry and Enoka, 2007), and thus researchers have been working on more effective ways to assess and quantify this important neuro-physiological event by exploring the mechanisms of fatigue and analysing fatigue-induced movement alterations. Apart from the subjective scales such as visual analogue scale (VAS) used for evaluating perceived fatigue (Lee et al., 1991), traditional objective biomechanical methods, including force-output measurements, kinematic variables, surface electromyographic (sEMG) metrics, and physiological indicators, are commonly used for fatigue assessment. Among these, the sEMG signal can reflect both biochemical and physiological information, making it a useful tool for evaluating muscle activation changes during fatigue.

Muscle fatigue reduces the amplitude of the sEMG signal at maximum voluntary contraction (MVC; (De Luca, 1984)). Decreases in sEMG frequency components have also been widely observed during the fatigue progress, as muscle fibre conduction velocity (CV)

declines and the low-pass effect of the sEMG conductivity through tissue allows for relatively more low frequency components to be detected at the skin surface (Cifrek et al., 2009; González-Izal et al., 2012; Potvin and Bent, 1997). Several research groups interpreted these overall trends as myoelectric manifestations of fatigue (MMF) and used them to evaluate the intensity of the movement task (Antwi-Afari et al., 2017; Mahdavi et al., 2018; Yin et al., 2019). Some researchers have also interpreted the corresponding alterations in movement kinematics (Ebenbichler et al., 2017; Song et al., 2009) and investigated motor control and movement coordination (Ebenbichler et al., 2017). Nevertheless, it is worth noting that the nonstationary nature of the dynamic sEMG signal may complicate the reliability and validity of traditional spectral estimation techniques; therefore, nonstationary signal-specific analysis methods should be applied to extract more salient frequency information (Cifrek et al., 2009; Ebenbichler et al., 2002; González-Izal et al., 2012; Knaflitz and Bonato, 1999). The continuous wavelet transform (CWT) has been proposed in recent decades to overcome the limitations of the traditional time-frequency transformation, which fails to achieve good time and frequency resolution concurrently (Cohen, 1989). The unique frequency-focus adjustment helps this time-frequency CWT processing technique to accurately capture transient frequency information in non-stationary signals and makes it the optimal choice for detecting dynamic sEMG frequency components (Karlsson et al., 2000).

Several researchers have also used complexity methods to analyse sEMG signals and have observed a significant loss in complexity in the post-fatigue sEMG signal, which suggests these sEMG complexity metrics might provide new insights into the assessment of muscle fatigue (Rampichini et al., 2020). For example, both Xie et al. (2010) and Kahl and Hofmann (2016) applied a fuzzy entropy algorithm to the sEMG signals of the biceps muscle during voluntary isometric contractions and observed a similar decreasing trend of the mean frequency and other spectral metrics (i.e., spectral moments ratio and the wavelet method WIRM1551).

While most researchers have focused on the sEMG of isometric contractions, Hernandez and Camic (2019) analysed the different mechanisms of static and dynamic contractions. They compared the complexity of pre- and post- fatigue sEMG signals from the vastus lateralis during isometric, eccentric, and concentric contractions using sample entropy (SampEn) and detrended fluctuation analysis (DFA). Their results showed that the complexity of the sEMG signals during concentric contractions was the highest regardless of the algorithm used (Hernandez and Camic, 2019). Similarly, Liao et al. (2021) used modified SampEn (MSE; (Costa et al., 2002)) and spectral metrics to assess muscle fatigue and recovery during biceps curls. They demonstrated that MSE can be used for fatigue and recovery assessment and suggested that MSE is more sensitive to muscle fatigue than other spectral metrics and has better performance at detecting muscle recovery after cupping therapy (Liao et al., 2021).

Although entropy-based analyses seem to detect muscle fatigue efficiently, the algorithm's reliability and sensitivity need further validation. Among the few assessments of fatigue induced through dynamic contractions, the amount of studies that compared the use of entropy and spectral methods over time is limited. In addition, most studies used other sEMG metrics as the indicators of muscle fatigue and could only perform comparisons between pre and post fatigue due to the limitations of prolonged isometric contractions. Although sEMG entropy appears to correlate with the intensity of muscle contractions (Troiano et al., 2008; Zhu et al., 2013), its relation to other fatigue indicators, such as the increase in perceived fatigue or decline in force-output, still requires further evaluation.

1.2 Purpose

This thesis was designed to: 1) calculate and compare the major frequency components (MFC; (Graham et al., 2015)) and MSE of the sEMG signals during a repetitive trunk flexion-extension (F-E) task; and 2) determine which sEMG metric is more closely related to ground truth fatigue indicators including the visual analogue scale (VAS), maximum pulling force, and

kinematic variability of movements. Specifically, CWT and MSE methods were applied to the lumbar erector spinae sEMG to determine how the major frequency components and complexity of the signal change throughout a repetitive trunk F-E movement protocol, respectively. Repeated-measures correlations were then applied to the two sEMG metrics to determine their relationship, and between each sEMG metric and the subjective perception of fatigue (VAS), force output (maximum pulling force), and dynamic kinematic variability (SMCI) to find out which of these two sEMG metrics is more closely related to other fatigue indicators during the repetitive F-E movement protocol.

CHAPTER 2: LITERATURE REVIEW

2.1. The Mechanisms of Muscle Fatigue

The early studies defined muscle fatigue (or "performance fatigue") as the inability to perform an expected task or maintain a required amount of force, separating fatigue into two phases, "fatigued" and "not fatigued" by a certain "point of fatigue" (Bonato et al., 2002; Cairns et al., 2005; Potvin and Bent, 1997). Many researchers later realized that the process of muscle fatigue is similar to the concept of material fatigue: the final failure is a cumulative result of physiological and biomechanical changes led by fatiguing muscle contractions (Merletti et al., 2004; Song et al., 2009). In addition, the neuromuscular system also adopts various compensatory strategies to achieve the given task before reaching the point of failure (Monjo et al., 2015; Sparto et al., 1997). Therefore, the decline in mechanical power or force output could be regarded as the observable expression of fatigue in performance caused by progressive changes in many latent factors (Kent et al., 2016).

In modern studies, fatigue is commonly considered into two categories: central fatigue and peripheral fatigue (Merletti et al., 2004). Central fatigue refers to all the changes originating from the central nervous system (CNS) that affect downstream motoneuron activation (Gandevia et al., 1996). When performing fatiguing tasks, especially prolonged low-density exercises, the CNS adopts a protective strategy that eventually weakens the output and transmission of a central command. This could reduce the discharge rate and the recruiting number of motor units (Gandevia, 2001; Johnson et al., 2004), which may manifest as a decrease in muscle force production. During the fatiguing process, the CNS may also alter the muscle recruitment strategy to rebalance the force contribution among synergist and antagonist muscles, keeping the net force or torque output the same (Gandevia, 2001; Paillard, 2012). These alterations in motoneuron excitation may help minimize the probability of activation

failure (e.g., axonal branch-point failure) and optimize muscle activation (Barry and Enoka, 2007).

Peripheral fatigue is related to the impairment in muscle contractile mechanisms caused by peripheral electrophysiological adjustments (Boyas and Guével, 2011). Muscle contractions lead to high adenosine triphosphate (ATP) hydrolysis, which, combined with slowed blood flow, results in lactic acid accumulation, raising the concentration of intracellular hydrogen ions and inorganic phosphate. The imbalanced concentration of intra- and extra-cellular ions inhibits the release and reuptake of calcium ions at the sarcoplasmic reticulum and impairs their movements (Brody et al., 1991; Komi and Tesch, 1979). As a result, the neuromuscular transmission, muscle action potential propagation, excitation-concentration coupling, and corresponding contractile mechanisms are altered (Boyas and Guével, 2011; Kent-Braun et al., 2012). Many researchers have suggested that these phenomena could further reduce muscle force generation (Ament and Verkerke, 2009; Bigland-Ritchie et al., 1982; Boyas and Guével, 2011; Westerblad et al., 1998).

2.2 Muscle Fatigue in the Workplace

Muscle fatigue is becoming a concern in the workplace due to its short- and long-term health effects on workers. In the short term, muscle fatigue is associated with reduced performance, productivity, quality of work and increased accidental injury in the workplace (Kajimoto, 2008; Kumar, 2001; Yung and Wells, 2016). Muscle fatigue usually leads to changes in muscle recruitment strategies (Gandevia, 2001) and unbalanced loadings on each muscle due to the need to compensate for a reduction in strength and to complete the required task (Radwin et al., 2001). These fatigue-induced adjustments to motor control may result in an inconsistent motor behaviour (Monjo et al., 2015) and negatively impact dynamic stability (Asgari et al., 2017; Chan et al., 2020; Graham et al., 2012; Granata and Gottipati, 2008). Such a kinematic imbalance can cause overload on tissues, including muscles, tendons, and

ligaments, leading to overuse injuries (Everett, 1999; Kumar, 2001) and sprains and strains: the leading workplace injury in Ontario for the last 18 years (WSIB, 2022). Fatigued muscles also have a longer response time to perturbations, which further hinder individuals from coping with unexpected events while performing motor tasks and potentially cause slips, falls, and other workplace injuries (Parijat and Lockhart, 2008). Poor post-fatigue movement control indicates that muscle fatigue may be a potential factor in workplace accidents.

Insufficient recovery from those above-stated short-term muscle fatigue effects could result in long-term cumulative or chronic fatigue, which may further lead to tissue stress-bearing capacity decline (Kumar, 1990), immunodeficiency (Kajimoto, 2008), and work-related musculoskeletal disorders (WMSDs; Antwi-Afari et al., 2017; Everett, 1999; Nussbaum, 2001; Radwin et al., 2001; Tang, 2022). Similar to the process of material fatigue to failure, WMSDs are the accumulated result of long-term or repeated exposure to transient external loads within muscle tissue tolerance (Radwin et al., 2001), which is especially common in repetitive tasks (Dempsey, 1998; Mital et al., 1994; Nussbaum, 2001). WMSDs have caused great economic losses in various countries (Da Costa and Vieira, 2010; Kajimoto, 2008; Roquelaure et al., 2006). Understanding the mechanisms of fatigue and learning about the methods for assessing fatigue in the workplace can help mitigate the risk of WMSDs and increase task performance and productivity by designing more appropriate workloads, worker schedules, and training programs (Williamson and Friswell, 2013).

2.3 Methods for Assessing Muscle Fatigue

Quantifying fatigue is essential for fatigue assessment. However, *muscle fatigue* does not have a formal definition (Barry and Enoka, 2007). Regardless, there are various ways of quantifying fatigue: subjective scales for evaluating perceived fatigue, traditional objective biomechanical methods including force-output measurements, kinematic metrics, EMG metrics, and physiological monitors such as heart rate and oxygen consumption. From

exploring fatigue mechanisms to analysing fatigue-induced subjective/objective changes, researchers have been working on seeking more effective ways to assess and quantify this important neuromuscular phenomenon.

2.3.1 Subjective Rating Scale

Subjective scales are commonly used for quantifying an individual's perception of fatigue. As the state level of fatigue changes rapidly during dynamic tasks, corresponding measurements are usually easy and clear to complete without additional effort (Lee et al., 1991). The visual analogue scale (VAS) for fatigue usually consists of two endpoints, "not fatigued at all" and "extremely fatigued," connecting with a 100-mm line and no number index in between (Figure 1). Such a simple design makes the VAS easy to operate and time-efficient. Participants draw a single mark on the line to indicate their fatigue level at relevant time points. Blinding the participant from the previous scores to reduce bias and interference from earlier tests is an additional benefit of the VAS (Lee et al., 1991). Another popular method is Borg's Rating of Perceived Exertion Scale (Borg, 1982), which is a numerical scale that marks the level of exertion from "no exertion at all = 6" to "maximal = 20" (Table 1). Participants are usually asked to verbalize the number representing their fatigue level during the test. Borg's Rating of Perceived Exertion Scale has been shown to correlate well with a variety of fatigue indicators (e.g., force loss, sEMG root-mean-square; (Troiano et al., 2008)). The scale value can also be used to denote heart rates ranging from 60 to 200 beats per minute (BPM), which is designed to correlate linearly with exercise intensity and make scoring intuitive (Borg, 1982).

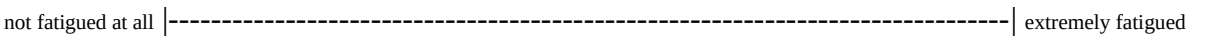

Figure 1. Visual Analogue Scale for fatigue.

Table 1. Borg rating of perceived exertion scale.

Score	Level of Exertion
6	No exertion at all
7	Very, very slight
8	
9	Very slight
10	
11	Fairly slight
12	
13	Somewhat severe
14	
15	Severe
16	
17	Very Severe
18	
19	Very, very severe (almost maximal)
20	Maximal

2.3.2 Objective Biomechanical Measurements

Loss in force-generating capacity is one of the most iconic factors related to fatigue; thus, it is common to assess fatigue via maximum force output (Vøllestad, 1997). This output capability can be captured in various forms, such as measuring the maximal force with a load cell. These maximal force tests are usually performed during isometric contractions where participants use all their strength against static resistance. The specific isometric contraction protocol may vary depending on the muscle or body region of interest (e.g., performing knee extensions to assess quadriceps strength (Yaggie and McGregor, 2002) or shoulder elevation to measure upper trapezius strength (Troiano et al., 2008)). One major limitation of the maximal force tests is that they cannot be performed during the task, which makes them inapplicable in real-time monitoring (Cheng and Rice, 2005; Williams and Ratel, 2009). Another major limitation is that performing the isometric contraction induces fatigue, making the mechanistic cause of the force reduction unclear (Abdel-Malek et al., 2021).

Increased movement variability (e.g., mean standard deviations; (Dingwell and Marin, 2006)) and reduced dynamic stability (e.g., increased Lyapunov exponent (Granata and Gottipati, 2008)) are widely observed during muscle fatigue, which can be quantified using

kinematic data and has the potential to be used as a real-time fatigue monitoring tool. Optical motion capture cameras and inertial measurement units (IMU) are two common motion capture systems used to collect kinematic data (Uchida and Delp, 2021). Traditional optical motion capture systems track the motion of the reflective markers placed on the participants and reconstruct the position and orientation of target body segments in space. The precision of the data largely depends on the recording devices (i.e., camera resolution, sampling rate, number, etc.) and the marker protocol (e.g., number, placement) (Uchida and Delp, 2021). IMUs, on the other hand, comprise accelerometers for measuring linear accelerations, gyroscopes for measuring angular velocities, and a magnetometer for measuring heading relative to magnetic north and provide the relative motion between the target body segments. Such a body-worn system eliminates the limitation of a laboratory environment and has become a popular, lower-cost alternative for quantifying movement (Uchida and Delp, 2021).

To analyse kinematic data, each body segment's centre of mass and the joint angle between adjacent segments are usually processed as descriptive statistics, which could be used for further calculations of variability and stability metrics (Robertson et al., 2014). For example, the Spine Motion Composite Index (SMCI; Equation (3); (Chan et al., 2020)) consists of ten kinematic variables (i.e., peak value of the thoraco-pelvic continuous relative phase, repetition time, and IMUs' orientation range, peak orientation, angular velocity, and angular acceleration) that are captured by two IMUs attached to two adjacent body segments (i.e., pelvis and T8 vertebrae) and can be used to quantify the changes in movement patterns at an individual level. By calculating the normalized deviation of the kinematic variables for each movement repetition relative to the participants' unfatigued "typical" movement patterns, SMCI could be applied to detect spine motion variation associated with muscle fatigue (Chan et al., 2020). Kinematic data provide a solution to observe and evaluate fatigue-induced movement changes in real time across the whole neuromuscular system. However, before the motion pattern

produces observable changes, muscle activation patterns will have already started changing, which further attracts researchers to assess muscle fatigue by measuring muscle activities.

Electromyography (EMG) provides a tool to understand fatigue at the muscular level. The EMG signal is a recording of the bioelectrical activity at the skeletal muscle level that conveys information about muscle contraction (Darmawan, 2004). Excited by the CNS impulse, the efferent signal, which conveys the control strategies of the CNS, transmits along peripheral nerve fibres, across neuromuscular junctions, and then excites motor units. The nerve impulse activates the membrane potential polarization and depolarization to generate an action potential. This series of ion events propagates along the muscle fibres in the form of an all-or-nothing response, producing a muscle contraction. During voluntary contractions, muscular force production is controlled by the combination of two processes: 1) recruitment, in which motor units are activated progressively according to the amount of force required and 2) firing, the pattern of which represents the frequency with which motor units are activated (Darmawan, 2004). Depending on the location of the electrodes, EMG can be divided into two types: intramuscular/indwelling EMG (usually applied to detect the action potentials of deep muscles) and surface EMG, which captures the sum of all muscle fibre electrical activities under the skin surface, where the cumulative motor unit action potential (MUAP) trains in time and space, filtered by the volume conductor of subcutaneous tissues such as fat and skin, are detected at the electrodes placed on the skin surface. sEMG is more widely used in research and applications due to its non-invasive advantages (González-Izal et al., 2012). Detailed sEMG methods are covered in the following section.

2.4 sEMG-Based Muscle Fatigue Assessment

2.4.1 Myoelectric Manifestations of Muscle Fatigue

The electrophysiological events occurring during muscle fatigue progression affect the MUAP waveform, which is captured by the sEMG signal as MMF (Merletti et al., 1990).

Traditional descriptors of sEMG signal in both time and frequency domains have been widely used for muscle fatigue assessment.

A decrease in the amplitude of EMG signal is considered an MMF, for it could be associated with declining muscle force output (Enoka et al., 2011; González-Izal et al., 2012). This estimation is in accordance with the intramuscular amplitude measurements of De Luca (1984). The mathematical model used by De Luca (1984) was based on the knowledge of the contraction mechanism. As mentioned above, fatigued muscle contractions could weaken both the firing rate and the recruitment of motor units, causing the MUAP amplitude to decrease (Merletti et al., 1990). It is attractive to use EMG amplitude to estimate muscle force; however, many researchers observed an increase in the fatigue sEMG amplitude during *in vivo* experiments (Komi and Viitasalo, 1976). In their later work, Basmajian and De Luca (1985) explained that the difference between the results is caused by the different EMG recording methods, as the combination of the left-shifting in the power spectrum and the low-pass effect on the conductivity tissue makes more low-frequency components detectable by the surface electrodes. In addition, there are many other factors that should be carefully considered. Since sEMG records the sum of all MUAP under the sensors, electrode placement is a concern (Vigotsky et al., 2018). Not only does the distance between detected motor units and electrodes affect EMG amplitude, but the overlapping of different phase MUAPs may also cause amplitude cancellation (Day and Hulliger, 2001). Moreover, alternate recruitments of motor units have been observed within the same muscle. This "motor unit rotation" strategy, along with enhancing the excitatory drive to the motoneuron pool, helps maintain the same muscle force output while leading to the unstable sEMG amplitude (Fallentin et al., 1993; Westgaard and De Luca, 1999). Muscle force production is also affected by the contraction type, muscle fibre type, and other properties, such as the combination of muscles (Khazan, 2013). Therefore, the sEMG amplitude may fluctuate during the fatigue process, and their use to assess muscle

fatigue could be unreliable. The variation of spectral parameters with fatigue progression, on the contrary, is relatively consistent.

In 1912, Piper (1912) observed a gradual “slowing” trend in fatigue sEMG signals, which could not be described by time domain metrics at that time. With the help of digital signal processing, researchers later found this “slowing” phenomenon relates to the sEMG signal power spectrum being compressed into lower frequencies during fatiguing progress (Chaffin, 1973; Cifrek et al., 2009; De Luca, 1984). The decrease in muscle fibre CV is generally considered the major factor of frequency compression. Caused by H+ accumulation in peripheral fatigued muscles, the low-pH and ion-imbalanced environment in sarcolemma increases the duration of intracellular action potentials, which plays a key role in muscle fibre CV reduction, and the lower frequencies of the sEMG signal power spectrum (Dimitrova and Dimitrov, 2003). The changes in motor unit recruitment patterns caused by central fatigue also contribute to shifting spectral components. A decline in motor unit firing rate is generally considered as the influence of fatigue at the spinal level on the downstream motoneuron pool (Gandevia, 2001).

Besides the firing rate, the progressively synchronized motor unit activity is also hypothesized to cause the observed signal spectral property change (Cifrek et al., 2009). According to their contraction speed and fatigability, motor units are categorized into Type I (slow-twitch, slow CV, and high fatigue resistance), Type IIa, and Type IIb (fast-twitch, fast CV, and relatively low fatigue resistance). Therefore, the slow-motor-unit-dominated fatigued muscles are prone to generate “slower” sEMG signals (Gandevia, 2001). Traditional spectral descriptors, such as the mean and median frequencies of the power spectrum, are commonly used as MMF to assess muscle fatigue (De Luca, 1984). It should also be mentioned that although the frequency of the fatigued sEMG signal power spectrum shifts toward lower frequencies, the low-pass effect of the subcutaneous tissues may allow more low-frequency

muscle activity signals to be detected by the surface electrodes. The whole power of the signal spectrum might remain stable (De Luca, 1984; González-Izal et al., 2010).

2.4.2 sEMG Signal Spectral Analysis during Isometric Contractions

Time-frequency transformation is the first step of analysing the sEMG signal in the frequency domain. Limited by the computational devices, the traditional Fourier-based transformation was widely used in the early spectral analyses of sEMG signals (Cifrek et al., 2009). The principle of traditional Fourier-based techniques is to decompose the original signal into a combination of several sinusoids of different frequencies, amplitudes, and phases. The result of a Fourier operation can be considered as the filtered output of those mono-frequency band-passes, which is calculated by the convolutional product of the original signal and the impulse responses of this filter. Hence, the power spectrum of the whole input signal segment could be calculated, and the frequency components of that segment are fixed at a particular time (Cohen, 1989).

2.4.3 Factors Affecting sEMG Variables during Dynamic Contractions

Interpreting sEMG signals is complicated by many factors. Since sEMG signals are recorded from the electrodes applied to the skin surface, they are sensitive to the anatomical and physical features of the participants and the properties of the electrode itself (Farina et al., 2002). Various studies, both simulations and experiments, have been done to analyse the influence of these factors. This section addresses those factors that should be especially considered during dynamic tasks.

One of the major concerns of collecting myoelectrical signals during dynamic contractions is their non-stationarity, which makes it difficult to extract the spectral descriptors with traditional Fourier-based techniques (Bonato et al., 2001). During static contractions, the EMG signals are assumed stationary in a wide sense. Therefore, the signal's power spectrum is considered constant within a certain time window, and these changes in statistical and

spectral descriptors can be tracked by analysing the signals within each sliding window. However, in dynamic contractions, many transient events happen simultaneously, such as the rapid recruitment and de-recruitment of motor units, changes in muscle fibre length and joint angle, and alternations in force/power output. These transient events may cause the MUAPs and their conduction environment to vary over time and contribute to the non-stationarity of the EMG signal (Knaflitz and Bonato, 1999). In this circumstance, the spectral properties of the signal may have sudden changes during a dynamic task, which requires advanced time-frequency techniques to get more reliable results (Karlsson et al., 2000; Karlsson and Gerdle, 2001).

Dynamic tasks also incur changes in physical parameters when recording the signals from the skin surface. Since the skin surface and muscles are not perfectly fixed together, the electrodes on the skin surface would glide above the muscle belly during muscle contractions, resulting in a change in the relative position and direction between the detection area and the muscle fibres to be measured. Electrodes shifting above the innervation zone or tendon regions would cause sudden changes in sEMG amplitude and misinterpretations of other metrics (Farina, 2006; Farina et al., 2001; Mesin et al., 2009). Therefore, it is essential to standardize the location of sEMG electrodes to mitigate these effects (Zipp, 1982). It should be mentioned that the power production process is accompanied by great heat generation, which induces sweat to accumulate between the skin surface and the electrodes. Fortunately, the sweat layer does not appear to impact the frequency parameters of the recorded sEMG signals, and its impairment of amplitude can be mitigated by using proper medical adhesives (Abdoli-Eramaki et al., 2012).

2.4.4 Traditional Fourier-based Time-Frequency Analysis

For a nonstationary signal such as an sEMG signal, if divided into time windows, each of which is sufficiently short to be assumed stationary, then the time-varying frequency

information can be obtained by applying Fourier transform to each segment (Karlsson et al., 2000). The Short-Time Fourier Transform (STFT) provides a viable solution to overcome the nonstationary signal by providing the frequency components of each time window, allowing spectral information to be tracked during dynamic contractions (Roy et al., 1998). Furthermore, the spectrogram, representing the signal energy distribution in a time-frequency plane, can be obtained. However, the Heisenberg uncertainty principle shows that high time and frequency resolution cannot be guaranteed simultaneously. The time and frequency resolutions of STFT highly depend on the choice of the window function: a narrow time window would allow the detection of instantaneous changes while the frequency resolution would be relatively lower, and a window peaked in the frequency domain would compromise its time resolution (Cohen, 1989).

2.4.5 Wavelet Transform

Much work has been done comparing methods to look for better time-frequency processing techniques and the sEMG parameters for dynamic sEMG signals (González-Izal et al., 2010; Rogers and MacIsaac, 2013). In recent decades, the wavelet transform (WT) has been proposed and overcame the limitations of the traditional time-frequency methods (Karlsson et al., 2000). Similar to the general time-frequency methods, WT techniques can be used to analyse the time-varying frequency components of nonstationary time series by decomposing the signal in a time-scale plane. The flexible wavelets family, which could adjust the length of the analysis window size according to each frequency band, enables these techniques to have good time resolution at high frequencies and good frequency resolution at low frequencies (Cohen, 1989). Inside of decomposing the signal into various sine waves, WT calculates the coefficient of the signal with a set of wavelets of various time scales. The wavelet is an oscillating zero-mean waveform with a limited time duration. By dilating and translating from one unique mother wavelet, wavelets with different frequency responses and locations allow

the signal to be decomposed in a time-scale plane (Roberto and Philip J., 2004), and the adjustment of the frequency focus to detect instantaneous components of the signal (Karlsson et al., 2000).

Dependent on the translation and scale parameter used in the transform, WT can be classified into two broad classes: the continuous wavelet transform (CWT) and the discrete wavelet transform (DWT). In this study, the CWT was applied to capture the simultaneous time-frequency information, especially abrupt time-frequency characteristics of the sEMG signal.

For a given time-continuous input signal $x(t)$, the CWT is defined as Equation 1:

$$CWT_x(a,\tau) = \int_{-\infty}^{\infty} x(t)\psi_{a,\tau}^*(t)dt \quad (1)$$

where *t* represents a time, $a \in R^+$ represents the scale parameter, and $\tau \in R$ represents the translation parameter. The *Morlet* wavelet family $\psi_{a,\tau}^*(t)$ applied in this study is obtained by scaling the zero-mean mother wavelet $\psi(t)$ at time τ and scale a (Equation 2):

$$\psi_{a,\tau}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-\tau}{a}\right),\ \psi(t) = \frac{1}{\sqrt{\pi}}e^{-t^2}e^{i2\pi f_0 t} \quad (2)$$

where $i = \sqrt{-1}$ and the dominant frequency $f_0 = 1$ were used in the computation. The sampling frequency f_s and pseudo-frequency f_a to scale a have an inversely proportional relation as Equation 3:

$$f_a = \frac{f_0}{a}f_s = \frac{f_s}{a} \quad (3)$$

Similar to the spectrogram of the Short-Time Fourier Transform, the wavelet transform's scalogram $SCAL_x(a,\tau)$ is the signal energy distribution after the wavelet transform along the time-scale plane at scale a and time τ, where the power *P* of the CWT is determined as the squared magnitude of the wavelet coefficients (Equation 4):

$$P = SCAL_x(a,\tau) = |CWT_x(a,\tau)|^2 \quad (4)$$

2.5 Complexity Analyses of Muscle Fatigue

While traditional linear analysis methods have been widely used to assess sEMG signals in various fatigue tasks, it is hypothesized that the myoelectric signals, representing the nonlinear electrical activities of the neuromuscular system, would be better modelled as a nonlinear dynamic system. In recent years, several studies have detected nonlinear properties of sEMG signals and observed a significant loss in the complexity of the post-fatigue signals. Some researchers also suggested that the nonlinearity of the sEMG signal might reveal muscle fatigue mechanisms that are beyond the ability of the traditional linear analysis and may be better suited for complexity analyses. However, the sensibility and reliability of applying nonlinear methods to investigate fatigue have yet to be rigorously evaluated (Rampichini et al., 2020).

2.5.1 sEMG Complexity

An sEMG signal is commonly simulated as a linear summation of the MUAP trains in time and space that is filtered by a volume conductor between muscle fibres and the detection electrodes. However, many physiological factors introduce non-linearity properties into EMG signals, such as the nonlinear muscle control process and the viscoelastic properties of AP conducting media, which make the traditional linear model inadequate for representing the underlying complex regulatory mechanism of the neuromuscular system (De Luca, 1979). Nieminen and Takala (1996) suggested that EMG signals should be modelled as outputs of a nonlinear dynamic system and found a decrease in EMG dimensionality during fatigue isometric contraction. Even chaotic behaviour of the EMG signal has been observed in the following studies (Bodruzzaman et al., 1992; Padmanabhan and Puthusserypady, 2004), which further determined its nonlinearity and complexity characteristics (De Luca, 1979). Therefore, nonlinear analysis methods might be more appropriate for studying myoelectric properties.

2.5.2 Complexity-based Analysis of Muscle Fatigue

Nonlinear complexity-based tools derived from recurrence plots, such as fractal analysis, entropy, recurrence quantification analysis (RQA), etcetera, provide new approaches to measure the motor control coordination variability (Preatoni et al., 2013) and assess muscle fatigue (Cifrek et al., 2009; Rampichini et al., 2020). Several studies have suggested that these methods might reveal properties of the sEMG signal that are beyond the ability of traditional linear analyses. For example, a linear decrease of Fractal Dimension (FD) was observed in the vastus lateralis sEMG signals during fatiguing isometric knee extension, suggesting the increasing self-similarity in the signal, which referred that FD seems to be a useful index of motor unit synchronization (Pethick et al., 2019). Sung et al. (2007) collected sEMG data from erector spinae muscles while participants were lying prone and holding a suspended position until they were completely exhausted. The researchers suggested that people with low back pain had significantly lower sEMG SampEn values than their healthy controls; however, groups could not be distinguished using mean frequency analysis (Sung et al., 2007). Their follow-up study on low back pain patients showed that SampEn had better between-day reliability than the commonly used power spectrum analysis, suggesting this method could outperform the traditional ones (Sung et al., 2010).

Similar to linear analysis methods, much of the previous literature using complexity analysis of sEMG signals focuses on isometric contraction tasks. However, unlike common findings in isometric contractions, no difference in SampEn values were found between the pre- and post-fatigue sEMG in a fatiguing cycling experiment (Lin et al., 2016). Hernandez and Camic (2019) suggested that "sEMG complexity is affected by fatigue status and contraction type, with the degree of fatigue-mediated loss of complexity depending on the type of contraction used to elicit fatigue." This remark coincides with the findings of Ebenbichler et al. (2017), who analysed EMG signals with root-mean-square and the instantaneous median

frequency (IMDF-EMG) and found both metrics significantly differed between the data from eccentric and the concentric contractions. The researchers concluded that the difference in neural control strategies for each type of muscle contraction can be reflected by the different values from the same sEMG parameters (Ebenbichler et al., 2017).

Overall, although some nonlinear methods seem to be effective in detecting changes in sEMG signals caused by isometric contractions, their utility during dynamic movements remains unclear.

2.5.3 Modified Sample Entropy

Derived from approximate entropy (Pincus, 1991), sample entropy (SampEn) analysis quantifies the regularity of a time series by evaluating the repeatability of the waveform in the time domain. For a time series of length *N*, SampEn is defined as the negative logarithm of the conditional probability that two *m*-point sequences within a matching tolerance *r* remain within the same tolerance when considering the following point *(m+1)* (Richman and Moorman, 2000). Therefore, the higher the SampEn, the lower the probability of time sequence matching, and the less regular the signal. From a physiological perspective, healthy biological systems generally show higher complexity than their more dysfunctional counterparts (e.g., elderly, injured (Dingwell and Marin, 2006; Goldberger et al., 2002)); lower entropy values could indicate the impairment condition in the corresponding muscles (e.g., fatigue).

The SampEn algorithm is calculated using equations 5-9 (Grassberger and Procaccia, 1983; Richman and Moorman, 2000). The intercept from a given time series of length *N*, $\{X(i), i = 1, \dots, N\}$, forms a series vector with *m* components as Equation 5:

$$x_m(i) = \{x(i+k), 0 \le k \le m-1\}, 1 \le i \le N-m \qquad (5)$$

compute the distance between any two vectors as $d_{ij} = \max\{|x(i+k) - x(j+k)|, 0 \le k \le m-1\}$, where $i \neq j$

For a vector $x_m(i)$, the number of vectors $x_m(j)$ that within matching tolerance of r ($d_{ij} \leq r$) is defined as $n_i^m(r)$; thus, the probability that two m-point sequences within a matching tolerance of r is defined as:

$$B^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} n_i^m(r) \quad (6)$$

likewise, $A^m(r) = \frac{1}{N-m-1}\sum_{i=1}^{N-m-1} n_i^{m+1}(r)$ is the probability of those two given vectors matching, considering the next point $x(m+1)$.

Therefore, sample entropy is defined as:

$$SampEn(m,r) = lim_{N\to\infty} - ln\frac{A^m(r)}{B^m(r)} \quad (7)$$

which is estimated by the statistic:

$$SampEn(m,r,N) = -ln\frac{A^m(r)}{B^m(r)} \quad (8)$$

With the advantage of independence from the signal length (Chen et al., 2009), SampEn is commonly used for analysing short datasets such as physiological signals. However, different signal sampling rates could lead to different interpretations of irregularities by the SampEn algorithm. Therefore, traditional algorithms might yield a relative SampEn value in fatigue signals, which leads to less accurate results when compared to non-fatigued sEMG signals.

To mitigate the interference of random components and to better detect the complexity property of the signal, a multiscale modified approach was proposed by Costa et al. (2002), where a time lag τ is introduced between the successive data points of the sequences to be compared, which could be estimated through the auto mutual information function of the time-series. Therefore, modified SampEn (MSE) is defined as Equation 9:

$$MSE(m,r,\tau,N) = -ln\frac{A^m(r)}{B^m(r)} \quad (9)$$

CHAPTER 3: METHODS

3.1 Participants

Seven male and five female university-aged participants were recruited from the Ottawa area. The sample size was decided based on a previous study with a similar task (Chan et al., 2020). All participants met the following inclusion criteria: 1) aged 19 years or above; and 2) no history of low back pain, musculoskeletal injury, or spine disorders. Participants were excluded if they answered "yes" to any of the questions on the first page of the Physical Activity Readiness Questionnaire for Everyone (PAR-Q+ 2021) (Warburton et al., 2011). This internationally renowned pre-participation screening questionnaire was selected to determine the holistic readiness of the participant to complete the experimental protocol and reduce the risk of potential injury from fatiguing and related accidents. Each participant provided written informed consent, which was approved by the University of Ottawa ethics board (Appendix A).

3.2 Study Design

Data collection for each participant took place on a single day. Upon arrival, participants were provided with the consent form and the PAR-Q+ before getting prepared for the data collection. If they agreed and were eligible to participate, they were further introduced to the details of the movement protocol and body dimensions (Table 2) were measured to scale the Xsens kinematic model (Xsens Technologies B.V., Enschede, Netherlands).

3.2.1 Participant Preparation

Participants were prepared for the placement of the EMG electrodes. Each site was shaved if necessary and cleaned with alcohol wipes. Two wireless Delsys Trigno Avanti EMG sensors (Delsys, Natick, USA) were attached to the right and left lumbar erector spinae (LES-

R and LES-L, respectively) of the participants (Figure 2; 3 cm lateral to L3 spinous process; Cholewicki and McGill, 1996). The EMG data were collected at 1920 Hz.

Once the EMG sensors were placed on the participant, they were outfitted with the Xsens MVN Link inertial measurement unit (IMU) suit. Using a specialized T-shirt and straps, nine IMU sensors were attached to the participants on the following anatomical locations: the head, sternum, and pelvis; bilaterally on the shoulders, upper arms, and forearms (Figure 3). Kinematic data were collected and transmitted using the Xsens MVN Link motion capture system with a sampling rate of 240 Hz. The sEMG and kinematic data were synchronously collected using Xsens MVN Analyze software (2021.2, Xsens, Enschede, Netherlands).

Table 2. Body dimensions for Xsens model scaling.

Dimension	Description
Body Height	Ground to top of head when standing upright
Shoe Length	Length of shoes
Shoulder Height	Ground to C7 spinal process
Shoulder Width	Right to left distal tip of acromion (acromial angle)
Elbow Span	Elbow Span Right to left olecranon in T-pose
Wrist Span	Wrist Span Right to left ulnar styloid in T-pose
Arm Span	Arm Span Tip of right fingers to tip of left fingers in T-pose
Hip Height	Hip Height Ground to most lateral bony prominence of greater trochanter
Hip Width	Hip Width Right to left anterior superior iliac spine
Knee Height	Knee Height Ground to lateral epicondyle on the femoral bone
Ankle Height	Ankle Height Ground to distal tip of lateral malleolus

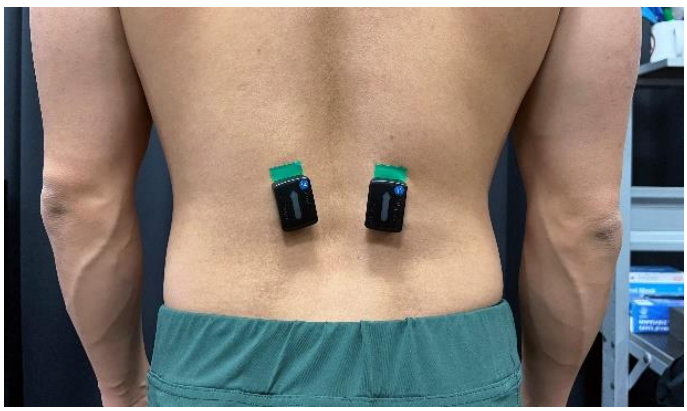

Figure 2. Surface electromyography sensor placement on the left and right erector spinae.

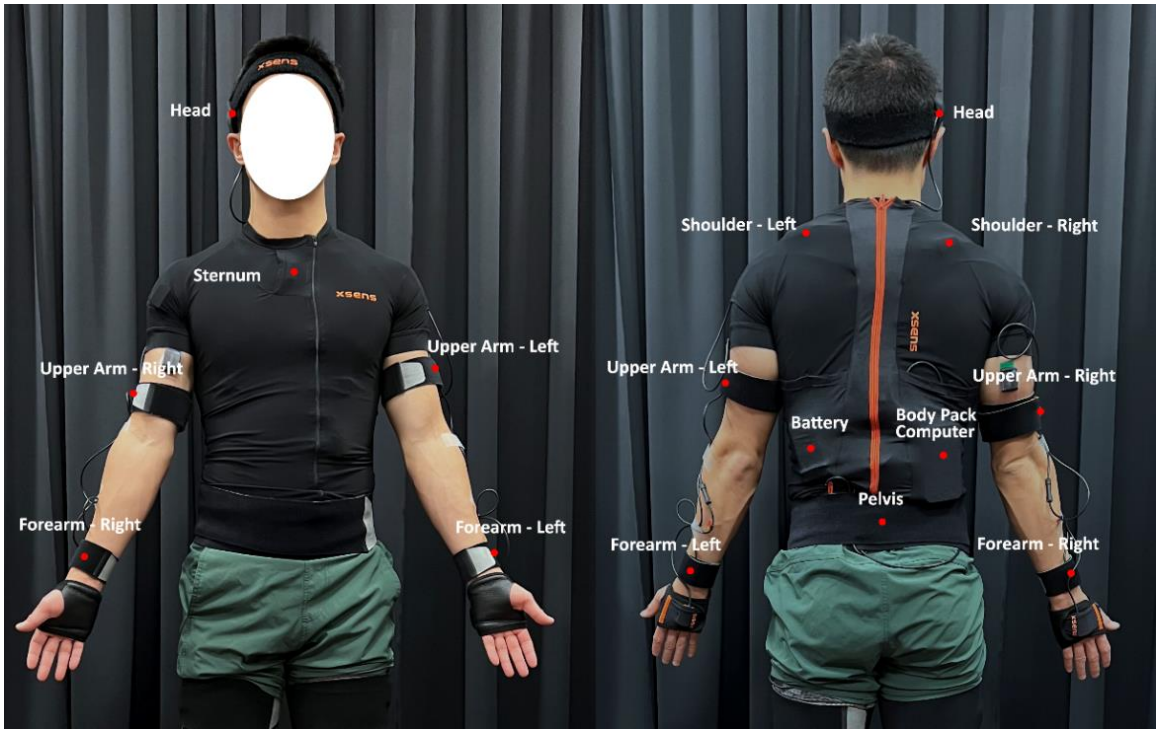

Figure 3. Xsens suit configuration with sensor placement. An upper body configuration (red dot) was used in this study for an upper body model without hands.

3.2.2 Movement Protocols

Participants were asked to complete one baseline set and twelve fatiguing sets of repetitive unloaded trunk F-E movements. The movement protocols were based on the protocols described in previous studies (Chan et al., 2020; Graham et al., 2014; Ross et al., 2015). Participants were instructed to repetitively touch two targets while restrained at the pelvis to restrict the movement of the lower limbs (Figure 4). The two targets were placed in the sagittal plane: one target was placed an arm's length away at shoulder height, and the other was placed at knee height, approximately 50 cm anterior to the knees. Participants were asked to keep their arms extended in front of them with their hands together throughout all repetitions. For each 50-rep trunk F-E fatiguing set, the two targets were alternately touched with the sound synchronized with a metronome set to 30 BPM (i.e., 0.25 Hz, 4 s per repetition). On the first beat of the metronome, the participants touched the target at shoulder height, touched the target at knee height on the second beat, and touched the shoulder target again on the third beat. This process was repeated for 50 repetitions.

After the preparation was completed, participants were instructed to familiarize themselves with the trunk F-E movement and tempo. They were asked to preform one set of the baseline protocol after the familiarization. A baseline fatigue assessment was taken directly after that, followed by a mandatory 8-minute rest period. Once rested, the fatiguing sets began; participants performed twelve trunk F-E movement sets with fatigue assessments done immediately between sets to avoid recovery. The study ended if any of the following four conditions were met: 1) they wished to stop; 2) they completed all twelve sets; 3) their fatigue VAS value reached the maximum; 4) their pulling strength became < 70% of their baseline value.

Figure 4. Participants performed the trunk flexion-extension task at 0.25Hz where they alternatively touched the upper (left) and lower (right) button to the beat of a metronome.

3.2.3 Fatigue Assessment

A modified fatigue VAS was applied to measure participants' perceived level of fatigue after every trunk F-E movement set. This simplified self-report scale consisted of two endpoints, "not fatigued at all" and "extremely fatigued," connected with a 100-mm line and

no number index in-between. Participants were instructed to complete their baseline value by anchoring the current fatigue level on the line with a pen. Once a scale was scored, it was covered immediately to avoid influencing the next measurement.

A maximum pulling strength test was also conducted as soon as the participant finished each movement set. Participants were asked to pull against an s-style load cell (60001A500-1000, Sensortronics, New Zealand) to determine their force-output ability. They were strapped at their pelvis and forced to use only their upper body strength to complete the pulling task with extended elbows. Participants were instructed to grasp the handle (Figure 5; adjusted to knee height) with both hands and gradually increase the force, pulling the handle upward until their maximum force was achieved; participants were instructed to maintain their maximum force for three seconds per attempt and complete it three times for each maximum pulling strength assessment. Participants were asked to perform the pulling with their self-selected gripping strategy and maintain this strategy throughout the study. The load cell data were read and collected by a computer through an analogue-to-digital board (NI USB-6363, National Instruments, USA) with a sampling rate of 100 Hz. The voltage output from the load cell was converted to Newtons using custom LabVIEW software (National Instruments, Austin, TX, USA).

One extra baseline fatigue assessment was taken before participants performed their very first set of the movement protocol. Their baseline pulling strength value was determined as the maximum value out of both baseline measurements (i.e., six values) since participants could have increased their performance after warming up.

Figure 5. Participants perform the maximum pulling strength test where they are strapped at the pelvis and thigh. The handle of the load cell is adjusted to their knee height.

3.3 Data Processing

3.3.1 Quantification of Fatigue

In this study, the fatigue VAS and maximal pulling strength were considered the fatigue level indicators for each participant. The fatigue VAS value for each measure was quantified by the researcher measuring the distance between the zero-lines and marks drawn by participants using a ruler with an accuracy of 0.1 cm (Appendix B). Participants pulled maximally three times for each maximum pulling strength assessment. The peak force for each attempt was averaged and then normalized by the baseline pulling strength value, resulting in one value per assessment.

3.3.2 sEMG Signal Pre-Processing

After the direct current bias removal, all sEMG signals were band-pass filtered between 30 and 450 Hz. The 30 Hz high-pass filter was applied to remove the electrocardiogram

artifacts, and the 60 Hz band-stop filter was used to remove power line interference. EMG data from each movement set was cut into 50 segments to represent each repetition (i.e., approximately 4s or 7680 data points per segment). The first ten flexion-extension repetitions of each set were excluded from analyses to ensure that participants achieved a steady-state movement pattern (Beange et al., 2019; Graham et al., 2014). All sEMG pre-processing and the following processing steps were performed using custom MATLAB software (R2018b, The MathWorks Inc., USA).

3.3.3 Spine Motion Composite Index

Ten kinematic variables in the sagittal plane were used to calculate the Spine Motion Composite Index (Chan et al., 2020) to quantify the subject-specific changes in movement patterns from their baseline movement set: peak value of the thoraco-pelvic continuous relative phase, repetition time, and IMUs (pelvis and T8 vertebrae) orientation range, peak orientation, angular velocity, and angular acceleration (Chan et al., 2020). In this study, the SMCI of each trunk F-E repetition was calculated and the average value from the last 40 cycles represented the kinematic variability for each movement set.

3.3.4 Major Frequency Components

In this study, the changes in sEMG signal frequency components were tracked by the major frequency calculated from their scalogram (Graham et al., 2015). As shown in Figure 6, the wavelet power scalogram of every five consecutive contractions was extracted. These scalograms with a length of 38,400 points were then re-mapped with 2D cubic interpolation into 401 points. For each F-E set of 40 repetitions, eight CWT scalograms were averaged, resulting in five complex major bursts for the whole set of data. To capture the frequency components of each plot, they were first converted from grayscale to binary using Otsu's method (Otsu et al., 1979) to determine the threshold. Then, the major sEMG frequency

components (MFC) of the F-E set were defined as the mean frequency value of the weighted centroid of five averaged bursts (Graham et al., 2015).

3.3.5 Modified Sample Entropy

In this study, the MSE from LES sEMG signals on both sides were calculated every trunk F-E repetition so that the data duration is comparable to the spectral analysis or entropy computation adopted in previous studies (Kahl and Hofmann, 2016; Liao et al., 2021; Xie et al., 2010). Then, the average of 40 MSE values were used to determine the mean MSE of each movement set. In the computation of MSE of all signal segments, the parameter values vector length $m = 3$, tolerance $r = 0.2 \times$ *standard deviation (SD)*, and time lag $\tau = 3$ were used according to pilot testing (Figure 7) and previous studies (Rampichini et al., 2020).

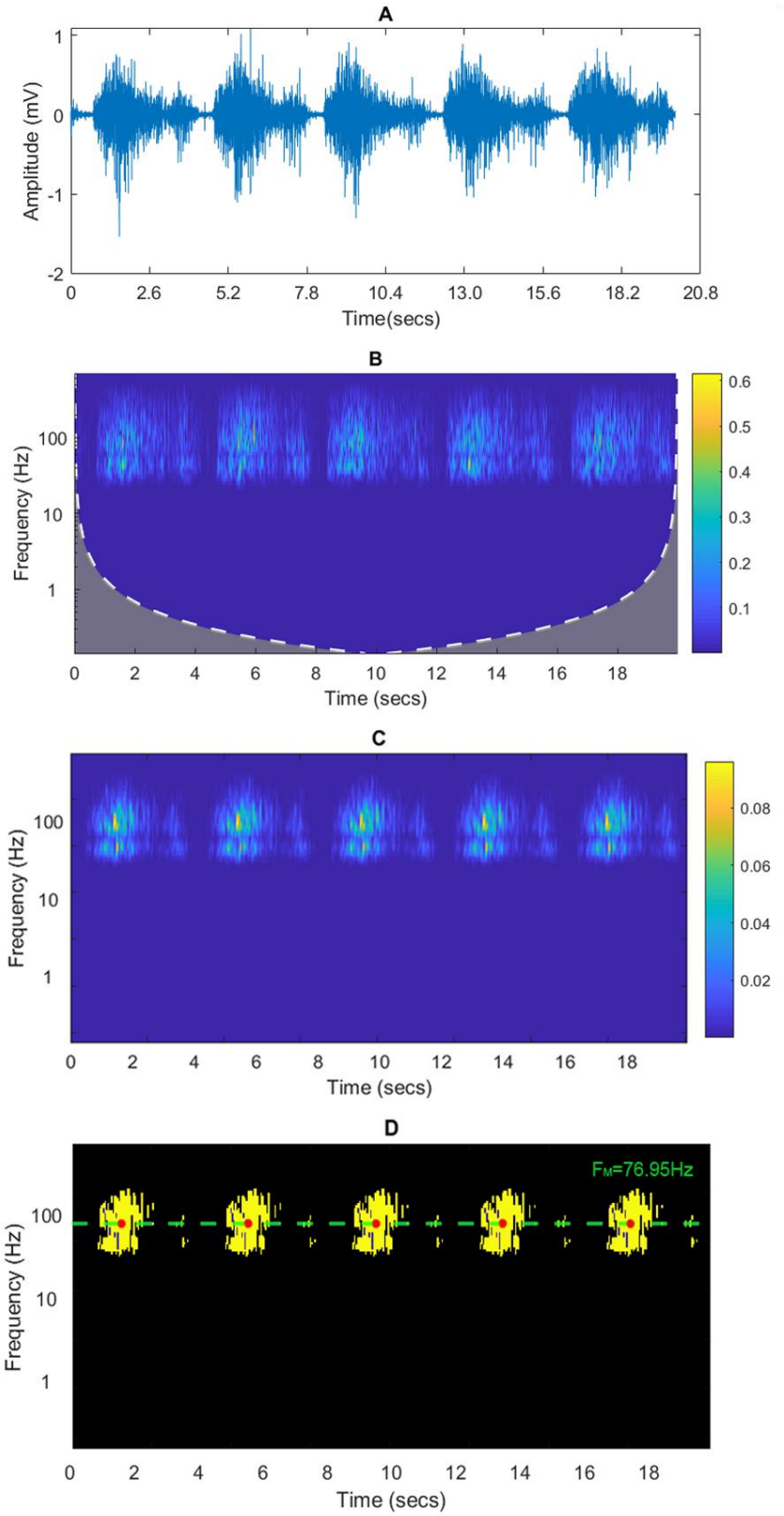

Figure 6. Major frequency components calculation example: (A) raw surface electromyography from the right lumbar erector spinae during five repetitions of a flexion-extension movement; (B) the scalogram of the sEMG after continuous wavelet transform; (C) the mean continuous wavelet transform scalogram of one set of flexion-extension movements; (D) the binary plot of continuous wavelet transform burst using Otsu's method, with red dots indicating the weighted centroids of the bursts and green line indicates as the mean frequency value (F_M).

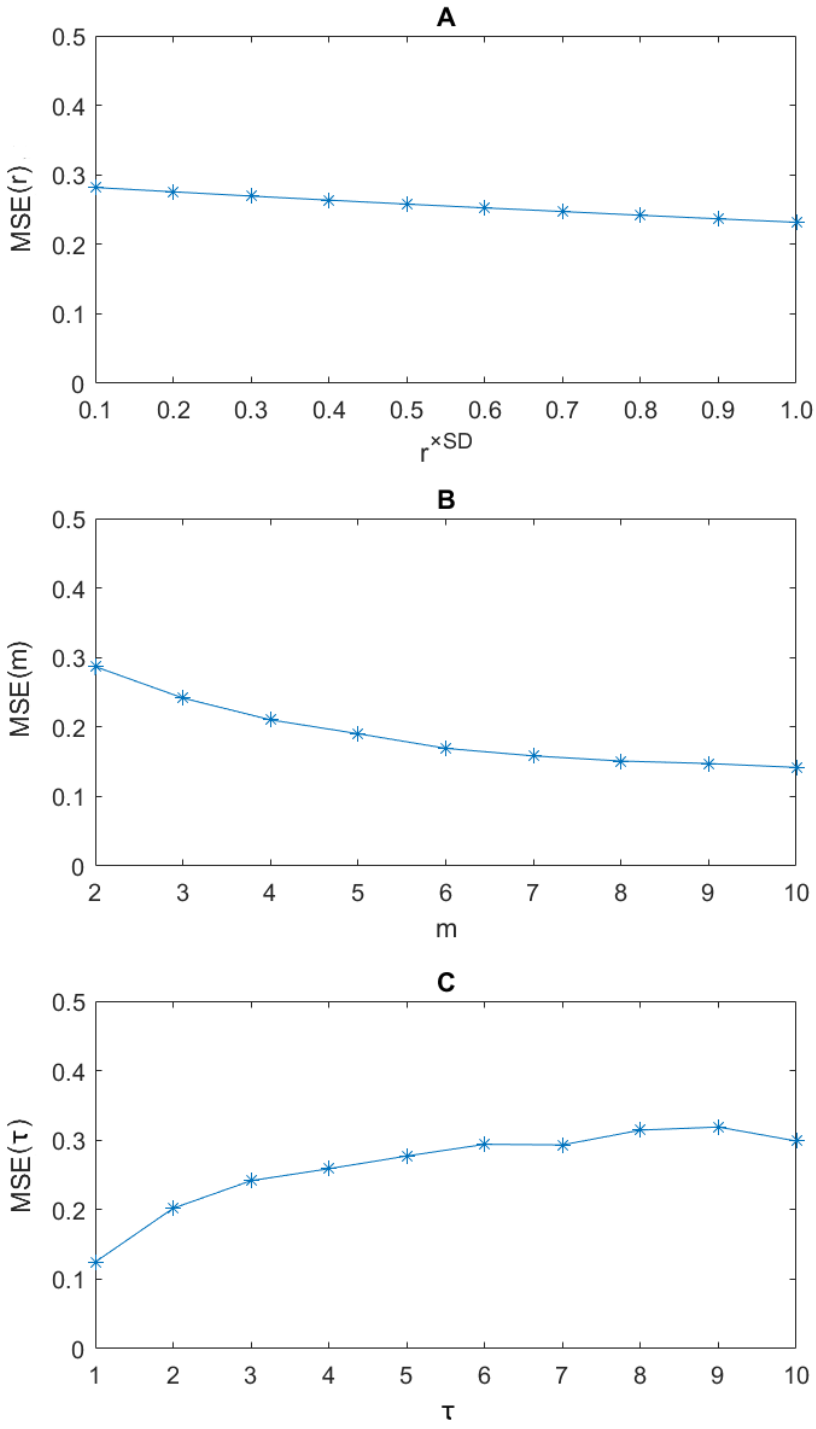

Figure 7. Modified sample entropy value (MSE) changing with parameters: (A) with varying tolerance *r* from 0.1 × *SD* (standard deviation of the signal segment) to 1.0 × *SD* (*m* = 3, *τ* = 3), MSE remains relative consistent. (B) MSE decreases with vector length *m* from 2 to 3 and then remains consistent (*r* = 0.2 × *SD*, *τ* = 3). (C) MSE rises with time lag *τ* from 1 to 3 and then reaches a plateau (*m* = 3, *r* = 0.2 × *SD)*.

3.4 Statistical Analysis

Repeated measures correlation coefficients (Bakdash and Marusich, 2017) were applied to measure the subject-specific correlations between the sEMG MFC and MSE, and their relationships with other fatigue measures (i.e., VAS, SMCI, maximum pulling strength). The correlation coefficient for each two indicators was calculated three times based on the participants' completion of the task: (A) across all participants; (B) across those who completed all of the 12 movement sets, and (3) across those who did not. All correlation calculations were performed using R (RStudio, R Core Team, Vienna, Austria). For all relationships, a correlation of 0.10–0.29, 0.30–0.49, and 0.5+ were interpreted as weak, moderate, and strong, respectively (Bakdash and Marusich, 2017).

CHAPTER 4: RESULTS

4.1 Participants

Participants' completion of the trunk F-E tasks is shown in Table 3. Six out of twelve participants finished all 12 sets of 50 trunk F-E movements, and the remaining participants dropped out after completing three to eight sets of the movement protocol. Among those who did not finish 12 movement sets, only one participant was forced to stop by the dramatic loss in force output ability. Others voluntarily discontinued the task due to perceived fatigue. All participants experienced a certain level of fatigue after finishing their movement protocol (VAS scored 85.2 ± 13.3). The SMCI showed an upward trend overall, indicating a gradual increase in the variability of participants' movement patterns during the fatiguing process. However, loss of pulling strength did not occur in every participant by the end of their data collection session (Figure 8).

Table 3. Completion of the movement protocol set.

Number of Flexion-Extension Sets Completed	Number of Participants (N)
12	6
8	1
6	1
5	1
4	2
3	1

4.2 Fatigue-led Changes in sEMG Metrics

The variations of each fatigue indicator and the two sEMG metrics with the number of completed movement sets are presented in Figure 9. Overall, on average, a visible decline in both sEMG MFC and MSE occurred during the fatiguing process. Some participants experienced visible decreases in their sEMG MFC and/or their sEMG MSE, while opposite trends in these EMG metrics were observed in other participants.

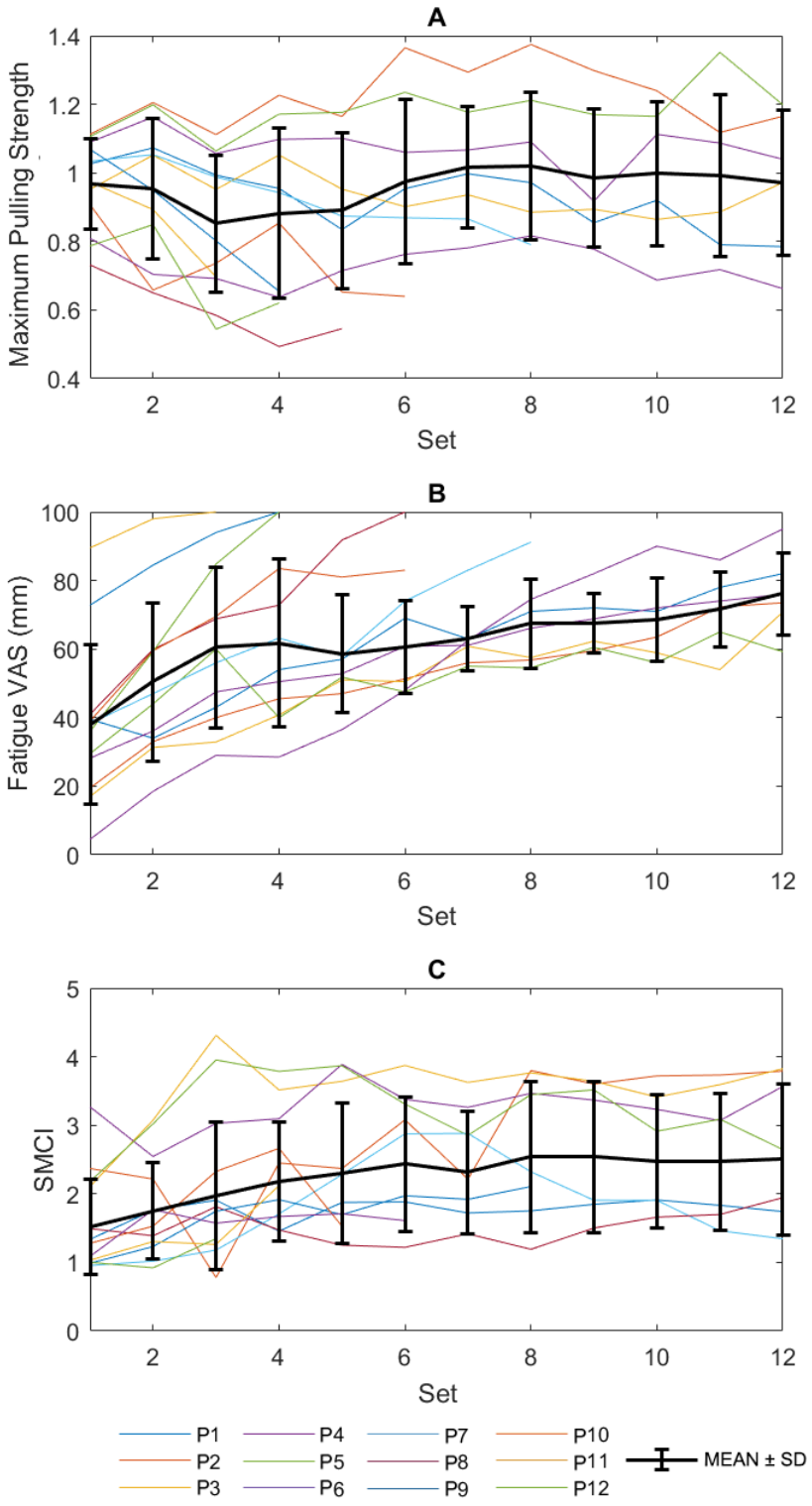

Figure 8. The value of fatigue indicators of each participant after completing each set of repetitive trunk flexion-extension movements. (A) maximum pulling strength; (B) fatigue visual analogue (VAS); (C) Spine Motion Composite Index (SMCI). Participants are identified as P1 to P12, error bars indicate as the standard deviation (SD) from the averaged value (MEAN) across participants.

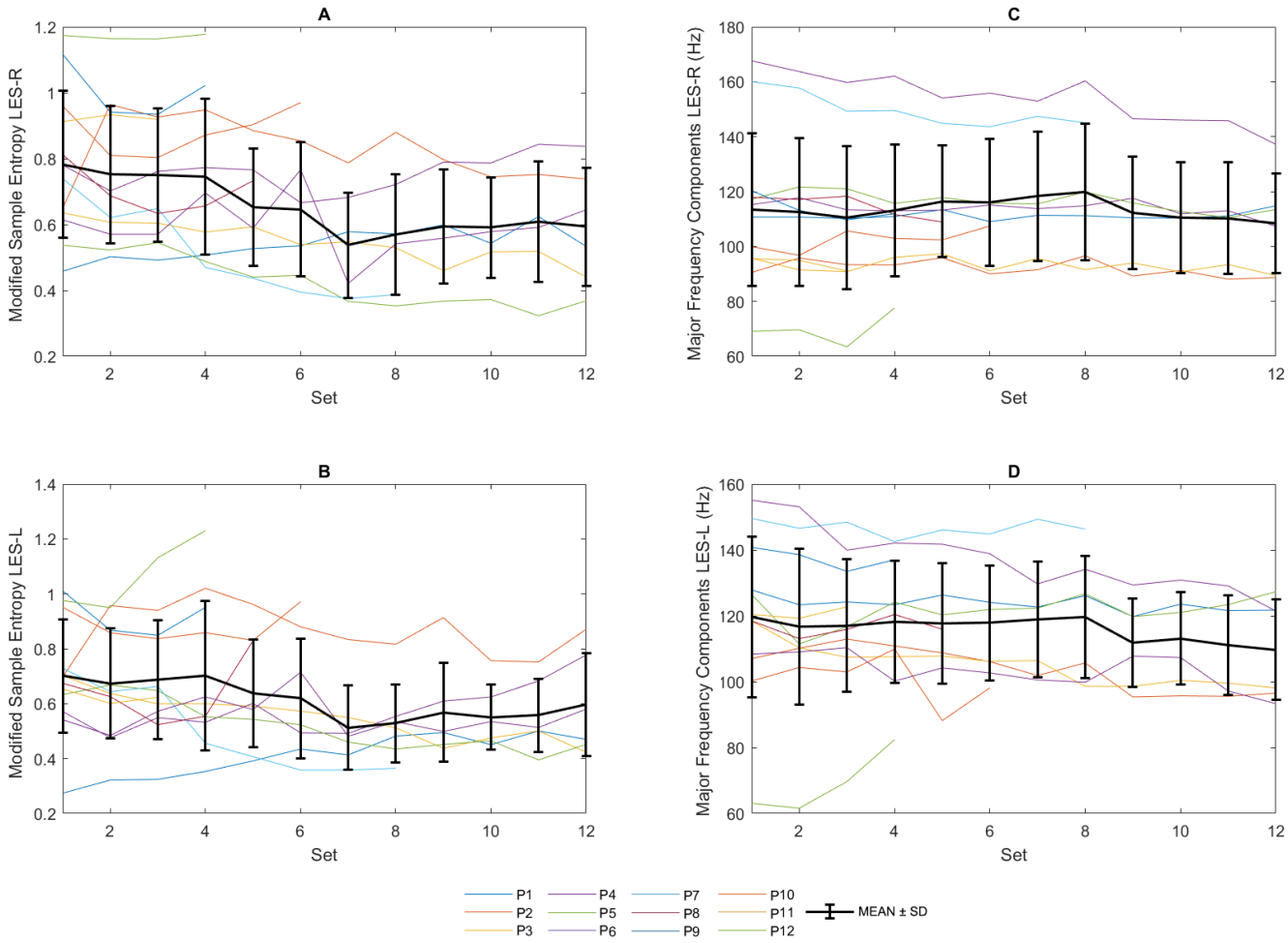

Figure 9. The results of sEMG metrics of each participant after completing each set of repetitive trunk flexion-extension movements. (A) modified sample entropy of right lumbar erector spinae (LES-R); (B) modified sample entropy of left lumbar erector spinae (LES-L); (C) major frequency components of right lumbar erector spinae (LES-R); (D) major frequency components of left lumbar erector spinae (LES-L). Participants are identified as P1 to P12, error bars indicate as the standard deviation (SD) from the averaged value (MEAN) across participants.

4.3 Correlation Between sEMG Metrics

The correlation coefficients of the repeated measures are presented in Table 4. Figure 10 shows the correlation plot for the repeated measures data, with 12 participants providing the same number of data points as the number of movements sets they completed. Each participant's data and corresponding best-fit line are shown in a different colour. A significant correlation was found between the sEMG MFC and their MSE during the fatiguing process ($r = 0.270$, $p = 0.005$).

4.4 Correlation Between sEMG Metrics and Fatigue Indicators

A strong, negative significant correlation was observed between the MFC and the fatigue VAS value among all participants ($r = -0.602$, $p < 0.001$) and among the six who finished all 12 trunk F-E sets ($r = -0.777$, $p < 0.001$). However, only a weak significant correlation was observed between the MSE and fatigue VAS value among all participants ($r = -0.248$, $p = 0.011$), with no significance in this result among participants that finished all 12 F-E sets ($r = -0.148$, $\rho = 0.211$) and moderate correlation among the participants who did not finish all 12 F-E sets ($r = -0.410$, $\rho = 0.022$).

Repeated measures correlation coefficients also showed a moderate correlation between the MSE and Spine Motion Composite Index, with $r = -0.335$ ($p = 0.001$) across all participants, $r = -0.242$ ($p = 0.048$) among participants who completed all movement sets, and $r = -0.624$ ($p < 0.001$) among the others who dropped in the middle of the session. A significant correlation was also found between the MFC and SMCI across all participants ($r = -0.269$, $\rho = 0.009$)

No significant correlation was found between the two sEMG metrics and the maximum pulling strength ($r_{MFC} = 0.100$, $p = 0.313$; $r_{MSE} = 0.193$, $p = 0.051$).

Table 4. The results of the repeated measures correlation coefficients between sEMG major frequency components (MFC) and modified sample entropy values (MSE) and other fatigue indicators: visual analogue scale (VAS), maximum pulling strength (Strength) and Spine Motion Composite Index (SMCI): (A) across all participants; (B) across those who completed all of the 12 movement sets and those who did not (C). * represents statistical significance at $p < 0.05$.

A

MFC	−0.602*	0.100	−0.269*	0.270*
MSE	−0.248*	0.193	−0.335*	
	VAS	**Strength**	**SMCI**	**MSE**

B

MFC	−0.777*	0.083	0.165	0.192
MSE	−0.148	−0.137	0.398*	
	VAS	**Strength**	**SMCI**	**MSE**

C

MFC	−0.113	0.165	−0325	0.473*
MSE	−0.410*	0.398*	−0.624*	
	VAS	**Strength**	**SMCI**	**MSE**

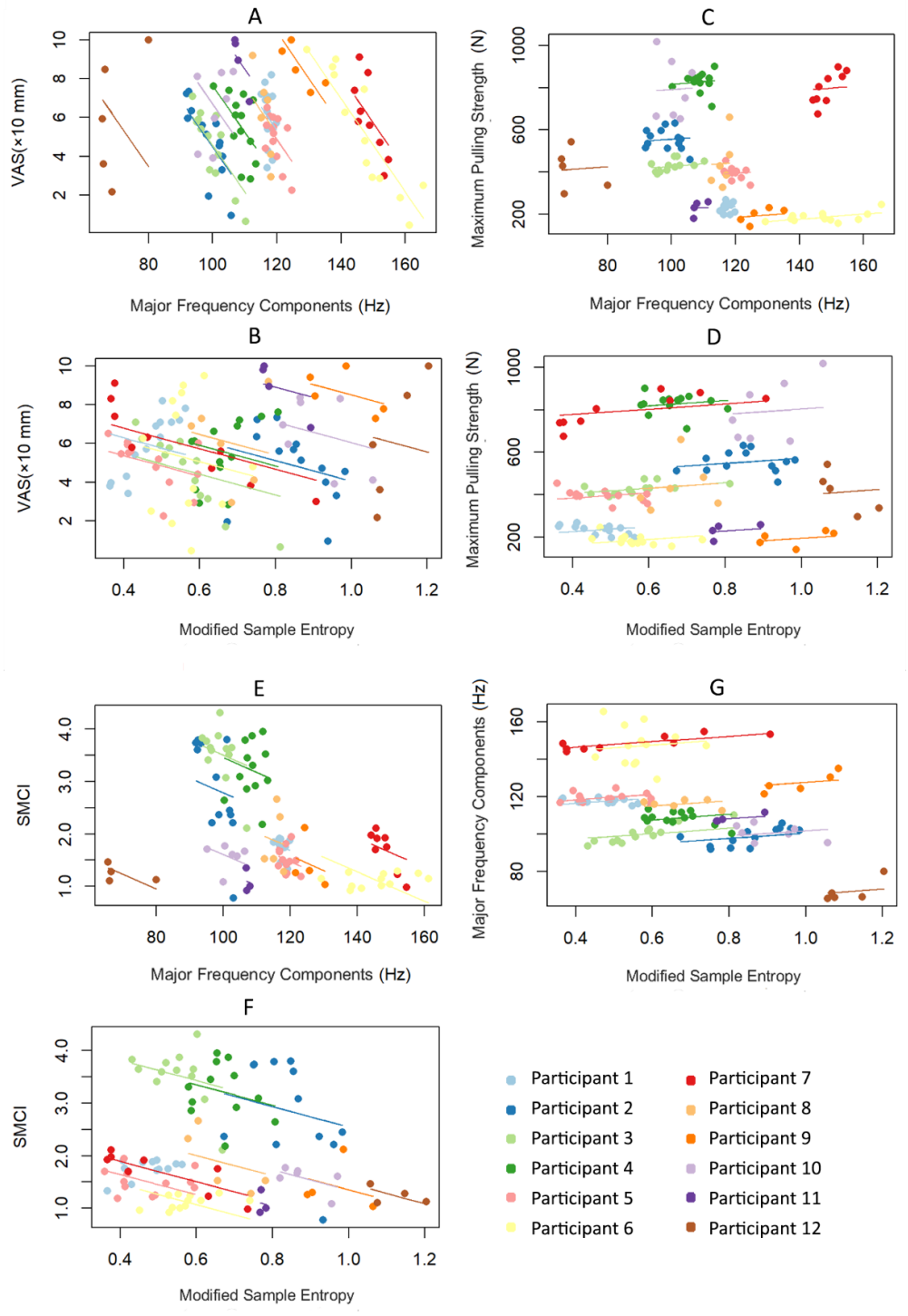

Figure 10. The repeated measures correlations plots of sEMG major frequency components and modified sample entropy values with other fatigue indicators: fatigue visual analogue scale (VAS), maximum pulling strength (unnormalized) and Spine Motion Composite Index (SMCI). The lines represent the line of best fit for the data of each participant.

CHAPTER 5: DISCUSSION

5.1 The Effects of Fatigue on sEMG Metrics

Before making comparisons, this study first determined the impact of fatigue during repetitive movement tasks on the metrics of the corresponding sEMG signal. With the increasing number of fatiguing movement sets being completed, declining trends of both sEMG metrics were observed at the group level and in many participants (Figure 9), suggesting both metrics can be used to detect MMF.

A decrease in the spectral descriptor value, such as the mean and median frequencies of the power spectrum, is commonly used as myoelectric manifestations to assess muscle fatigue (Cifrek et al., 2009; González-Izal et al., 2012). In this study, decreases in MFC were observed at the group level and among most participants, suggesting that CWT analyses can capture the spectral MMF and quantify muscle fatigue during complex dynamic muscle contractions. However, the relative decrease in this study was not as high as the results of previous studies (Graham et al., 2015). Such a difference could be caused by the more complex movement protocol, resulting in more adjustment freedom in the muscle activation strategies for participants to cope with the fatigue in the lumbar muscles. At the peripheral level, apart from the decreasing motor unit discharge rate, alterations in transmembrane electrolyte concentrations could also contribute to this trend. Caused by H+ accumulation, the low-pH and ion-imbalanced environment at the sarcolemma increases the duration of intracellular action potentials, which plays a key role in muscle fibre CV reduction and further, the sEMG power scalogram compressed into the lower frequencies (De Luca, 1984). Since spectral compression also increases the energy of low-frequency components, the whole power of the signal spectrum might remain stable (Dimitrova and Dimitrov, 2003). Extracting the MFC takes advantage of CWT scalogram and reduces the possibility of MMF misinterpretation.

Many participants in this study experienced a loss in their LES sEMG complexity as the MSE of the signal from their last movement set was lower than the initial set. Lower sample entropy values in the sEMG signal were widely observed after prolonged isometric contractions (Rampichini et al., 2020), suggesting the whole sEMG signal shifted into a more regular pattern (Navaneethakrishna et al., 2015). Repetitive fatiguing muscle contractions may lead to alterations in motor unit recruitment strategies and a reduction in muscle fibre conduction velocity (Cashaback et al., 2013; Tong et al., 2016), which could cause the observed drop in sEMG sample entropy value in this study. During muscle fatigue, the motor units discharge more simultaneously, which could lead to MUAP overlap, resulting in a smoother waveform for the aggregate signal on the skin surface (Tong et al., 2016). As a result of the metabolic and enzymatic processes during muscle contractions, the reduction in the CV may also smoothen the abrupt changes of the discharged MUAPs (Cashaback et al., 2013; Tong et al., 2016). Therefore, the complexity of the entire sEMG signal may decrease in the end due to dynamic fatiguing muscle contractions.

The declining trend of the MSE showed visible fluctuations set by set, suggesting the fatigue-led decrease in sEMG complexity may not be a monotonic tendency during complex dynamic muscle contractions. Previous studies have found that sEMG complexity could be task-dependent (Vaillancourt and Newell, 2002) and vary among muscle contraction types (Hernandez and Camic, 2019). In this study, three participants experienced a lumbar erector spinae MSE increase as the number of F-E tasks completed progressed. Such a countertrend may have occurred for various reasons. For one, the multi-joint trunk F-E task itself could be considered more complicated than maximal isometric contractions or single extremity movements adopted by previous studies (Rampichini et al., 2020). A study by Babault et al. (2022) also found that SampEn is sensitive to detect the sEMG complexity increases after the muscles warmed up. During submaximal contractions, the motor unit firing rate may first

decrease and then increase to maintain a constant output, which could lead to the SampEn of the EMG signal going up (Adam and De Luca, 2005). Also, Troiano et al. (2008) suggested that submaximal voluntary contractions may generate more "central" fatigue rather than "peripheral" fatigue (Søgaard et al., 2006), which may lead to participants potentially underestimating themselves and requiring early termination of the movement tasks. Therefore, although some participants perceived a high level of fatigue, their ability to generate force may not have been altered. Hernandez and Camic (2019) also suggested that "sEMG complexity is affected by fatigue status and contraction type, with the degree of fatigue-mediated loss of complexity depending on the type of contraction used to elicit fatigue." Though strapped at the pelvis, the increasing SMCI suggested that participants were still able to alter their motor strategy due to perceived fatigue to complete the trunk F-E task to the beat of the metronome.

5.2 The Relationship between two sEMG Metrics

Though both metrics show a decreasing trend as participants progressively fatigued, the weak correlation between the MSE and MFC of lumbar erector spinae sEMG signal also indicates that those two sEMG metrics are affected differently during the fatiguing process. Many participants experienced a fluctuation in the MSE of their sEMG signal during the movement protocol. A fluctuating upward trend of MSE also existed among four out of twelve participants during the fatiguing process. While a gentle increase of MFC was also observed in two of the twelve participants, all the others showed a moderate downward slope or remained constant. Considering all the nonlinear physiological metabolic activities and motor unit behaviours during muscle contractions, as well as the viscoelastic properties of conducting tissue (De Luca, 1979), the regulation strategies of muscle contraction to muscle fatigue may appear more variable. Differences in MSE fluctuation patterns (decrease, increase, or relatively consistent) and fatiguing muscles (LES-L and/or LES-R) between participants may result from

the different response strategies for the same task adopted by individuals, which may be beyond what conventional frequency analysis can reveal (Chakraborty and Parbat, 2017).

5.3 The Relationship between sEMG Metrics and Other Indicators

The second objective of this study was to determine the relationship between these two sEMG metrics and other fatigue indicators to discover which metric is more suitable for tracking myoelectric fatigue during dynamic muscle contractions.

In this study, both sEMG metrics were significantly correlated with individual perceived fatigue values (i.e., VAS). Contrary to the weak correlation between VAS and MSE, a strong correlation was found between the VAS and MFC. Spectral metrics have always been considered as important indicators of muscle fatigue (Bonato et al., 2001). In this study, most participants' sEMG MFC gradually decreased with increasing perceived fatigue. Consistent with previous research with spectral EMG variables (González-Izal et al., 2012), MFC may be used as an indicator of fatigue in multi-joint dynamic movement tasks as well.

No significant correlation was found between the maximum pulling strength and both of the sEMG metrics, likely because the maximum pulling strength for most participants did not appear to fluctuate throughout the study. In this study, although all the participants were strapped at the pelvis and intructed to only use their strength from the back and maintain the same pulling strategy throughout the study, it is possible that participants subconsciously adjusted their muscle recruitment strategies to achieve a higher power output when feeling fatigued (e.g., increasing the contributions from the upper extremities). Additionally, the sEMG metrics were calculated from the signals recorded during the trunk F-E in this study, while the maximum pulling strength tests were performed after each movement set (i.e., they were not measured concurrently to the maximal pulls). The MCF and MSE might be unlikely to directly reflect the muscle activation characteristicss during the isometric pulling. To see traditional sEMG spectral methods (i.e., mean and median frequency) during this task, please see

Appendix C. In a submaximal isometric contractions study, Troiano et al. (2008) observed sEMG sample entropy being significantly related to force output rather than the participant's perceived fatigue. Another possible reason for such differing results could be explained by the different muscle contraction types of the sEMG. During the more variable dynamic muscle contractions, motor units may have more freedom to adjust their recruitment strategies and reconstruct the system dynamics to facilitate an effective response specific to a given task (Hernandez and Camic, 2019).

Both sEMG MSE and MFC showed a significant correlation with the subject-specific kinematic variability score. Fatigue has been associated with an increase in variability (Chan et al., 2020) and a decrease in stability (Cholewicki and McGill, 1996; Graham et al., 2012; Granata and Gottipati, 2008) during repetitive trunk movement tasks. On the other hand, muscle activation patterns and biomechanical coordination strategies may start adjusting at the earliest stages of fatigue to maintain movement stability (Gates and Dingwell, 2010; Graham et al., 2014). Therefore, in this study, the spine variability (presented as SMCI scores) increased with fluctuations for most participants. Similarly, more fluctuating changing trends were observed in sEMG MSE, suggesting that muscle motor unit recruitment strategies may constantly adjust to carry on the trunk F-E task while also matching the metronome. On the other hand, previous studies suggested that an increase in antagonistic muscle co-contractions may also contribute to maintaining the local dynamic stability of low back (Graham et al., 2014) as well as the movement accuracy during fatigue (Missenard et al., 2008), which might also explain why there is only weak correlation between the lumbar erector spinae sEMG MFC and the spine kinematic variability score.

5.4 Contributions

The study aims on filling the gap of tracking sEMG complexity during muscle fatiguing progress by comparing the sEMG MFC and MSE throughout multi-joint dynamic tasks. The

study found that with perceived fatigue increasing, a significant correlation was found between the two sEMG metrics. The study also revealed that although both sEMG metrics mapped onto the perceived fatigue and movement pattern variations during the task, the MFC had a stronger correlation with participants' perceived fatigue whereas MSE was more strongly correlated with kinematic variability. These novel findings suggest that the complexity metrics might be able to provide additional information on changes in muscle contraction patterns with fatigue progression, allowing for future studies to focus on the complexity changes in sEMG signal during dynamic contractions and further analyze these phenomena.

5.5 Limitations and Future Directions

In this study, the maximum movement protocol for the participants was 12 sets, which was based on the previous study where ten participants could finish all ten movement sets and experienced an increase in their perceived fatigue and a decrease in pulling strength (Chan et al., 2020). However, in this study, some participants suggested that they were 'not that fatigued' and would like to carry on the protocol after completing all 12 movement sets. Meanwhile, five participants decided to stop their protocol since they felt too fatigued. It is unknown the level of performance fatigue of those who experienced early perceived fatigue since their lifting strength remained stable and they were able to maintain the pace of the metronome (0.25Hz). One participant was forced to stop the movement protocol after they experienced a dramatic loss in strength. The great difference in perceived and performance fatigue levels among the participants in this study was not expected before recruitment. Considering the differences between participants who finished all 12 movement sets and those who did not, comparisons between different groups of participants could have provided more potential information. In future work, the maximum movement protocol should be increased, and more participants should be recruited to provide enough power for statistical tests to allow for the analysis between participants who reach different ending conditions (experience early perceived fatigue,

are able to complete all movement sets, reach the maximum of perceived fatigue, experience dramatic strength loss; section 3.2.2.).

Second, the number of participants recruited for this study is limited. There were only 12 participants recruited in this study since this sample number was considered to have the statistical power needed to test if the studied sEMG metrics are significantly affected by muscle fatigue, with the assumption that every participant could finish all 12 sets of the movement protocol. However, during the data collection, six participants completed all 12 sets of movement protocol, with the remaining six completing a variable number of sets. The pre-set participant number was not sufficient to perform statistical tests between different subject groups. Although both sEMG metrics showed significant changes during fatigue progress and have good correlation with other fatigue measures in this study, future efforts should evaluate if these correlations hold across a larger participant population.

Third, only the sEMG from both sides of the lumbar erector spinae was included in this study, as LES is the main muscle for back extension. Since the participants could change their technique to carry on the dynamic movement protocol, other synergistic muscles (e.g., the gluteal muscles) could be considered in future work to assess the adjustments in muscle strategies against fatigue during dynamic movements. Also, the data from muscles that perform trunk flexion (i.e., the abdominal muscles) were not included in this study. It would be interesting to compare how antagonistic muscle pairs alter together during the fatigue progress. Including other muscle activation signals could provide other perspectives for interpreting the impact of muscle fatigue on LES sEMG metrics.

In addition, although the sample entropy algorithm is robust to the signal length and could avoid the drawbacks caused by the self-matching in the approximate entropy algorithm, Xie et al. (2010) proposed a fuzzy approximate entropy algorithm for noisy and short datasets. They suggested that the new algorithm has better consistency and has a good correlation with

force output (Zhu et al., 2017). However, the high computational effort of fuzzy entropy precludes the use of this approach in practice at the moment. Further, comparisons are required to determine which algorithm is better suited for detecting MMF during dynamic contractions.

CHAPTER 6: CONCLUSION

Performing repetitive trunk F-E tasks lead to an increase in the participant's perceived fatigue, which may also result in a decrease in sEMG MFC and MSE value. This study showed the two sEMG metrics were significantly correlated with each other during the fatiguing progress and both sEMG metrics mapped onto the perceived fatigue and movement pattern variations during the task, suggesting they could be used for assessing fatigue during dynamic movements. However, the MFC had a stronger correlation with participants' perceived fatigue whereas MSE was more strongly correlated with kinematic variability. Continued research is required to further examine these relationships, as well as determine the best method of assessing changes in force output with muscle fatigue.

References

Abdel-Malek, D.M., Foley, R.C.A., Wakeely, F., Graham, J.D., Delfa, N.J. la, 2021. Calibrating ratings of perceived fatigue relative to objective measures of localised muscle fatigue using a feedback-based familiarisation protocol. Theor Issues Ergon Sci 22, 511–527. https://doi.org/10.1080/1463922X.2020.1827079

Abdoli-Eramaki, M., Damecour, C., Christenson, J., Stevenson, J., 2012. The effect of perspiration on the sEMG amplitude and power spectrum. Journal of Electromyography and Kinesiology 22, 908–913. https://doi.org/10.1016/j.jelekin.2012.04.009

Adam, A., De Luca, C.J., 2005. Firing rates of motor units in human vastus lateralis muscle during fatiguing isometric contractions. J Appl Physiol 99, 268–280. https://doi.org/10.1152/japplphysiol.01344.2004

Ament, W., Verkerke, G.J., 2009. Exercise and fatigue. Sports Medicine 39, 389–422. https://doi.org/10.2165/00007256-200939050-00005

Antwi-Afari, M.F., Li, H., Edwards, D.J., Pärn, E.A., Seo, J., Wong, A.Y.L., 2017. Biomechanical analysis of risk factors for work-related musculoskeletal disorders during repetitive lifting task in construction workers. Autom Constr 83, 41–47. https://doi.org/10.1016/j.autcon.2017.07.007

Asgari, N., Sanjari, M.A., Esteki, A., 2017. Local dynamic stability of the spine and its coordinated lower joints during repetitive Lifting: Effects of fatigue and chronic low back pain. Hum Mov Sci 54, 339–346. https://doi.org/10.1016/j.humov.2017.06.007

Bakdash, J.Z., Marusich, L.R., 2017. Repeated measures correlation. Front Psychol 8, 1–13. https://doi.org/10.3389/fpsyg.2017.00456

Barry, B.K., Enoka, R.M., 2007. The neurobiology of muscle fatigue: 15 years later. Integr Comp Biol 47, 465–473. https://doi.org/10.1093/icb/icm047

Basmajian, J. v., De Luca, C.J., 1985. Muscles alive: Their functions revealed by electromyography, 5th ed, Williams & Wilkins. Williams & Wilkins, Baltimore. https://doi.org/10.1093/ptj/54.10.1137b

Beange, K.H.E., Chan, A.D.C., Beaudette, S.M., Graham, R.B., 2019. Concurrent validity of a wearable IMU for objective assessments of functional movement quality and control of the lumbar spine. J Biomech 97, 109356. https://doi.org/10.1016/j.jbiomech.2019.109356

Bigland-Ritchie, B., Kukulka, C.G., Lippold, O.C., Woods, J.J., 1982. The absence of neuromuscular transmission failure in sustained maximal voluntary contractions. J Physiol 330, 265–278. https://doi.org/10.1113/jphysiol.1982.sp014340

Bonato, P., Boissy, P., Della Croce, U., Roy, S.H., 2002. Changes in the surface EMG signal and the biomechanics of motion during a repetitive lifting task. IEEE Transactions on Neural Systems and Rehabilitation Engineering 10, 38–47. https://doi.org/10.1109/TNSRE.2002.1021585

Bonato, P., Roy, S.H., Knaflitz, M., De Luca, C.J., 2001. Time frequency parameters of the surface myoelectric signal for assessing muscle fatigue during cyclic dynamic contractions. IEEE Trans Biomed Eng 48, 745–753. https://doi.org/10.1109/10.930899

Borg, G.A., 1982. Psychophysical bases of perceived exertion. Med Sci Sports Exerc 14, 377–81. https://doi.org/10.1249/00005768-198205000-00012

Boyas, S., Guével, A., 2011. Neuromuscular fatigue in healthy muscle: Underlying factors and adaptation mechanisms. Ann Phys Rehabil Med 54, 88–108. https://doi.org/10.1016/j.rehab.2011.01.001

Brody, L.R., Pollock, M.T., Roy, S.H., De Luca, C.J., Celli, B., 1991. pH-induced effects on median frequency and conduction velocity of the myoelectric signal. J Appl Physiol 71, 1878–1885. https://doi.org/10.1152/jappl.1991.71.5.1878

Cairns, S., Knicker, A., Thompson, M., Sjøgaard, G., 2005. Evaluation of models used to study neuromuscular fatigue. Exerc Sport Sci Rev 33, 9–16.

Cashaback, J.G.A., Cluff, T., Potvin, J.R., 2013. Muscle fatigue and contraction intensity modulates the complexity of surface electromyography. Journal of Electromyography and Kinesiology 23, 78–83. https://doi.org/10.1016/j.jelekin.2012.08.004

Chaffin, D.B., 1973. Localized muscle fatigue — Definition and measurement. Journal of Occupational Medicine 15, 346–354.

Chakraborty, M., Parbat, D., 2017. Fractals, chaos and entropy analysis to obtain parametric features of surface electromyography signals during dynamic contraction of biceps muscles under varying load, in: 2017 2nd International Conference for Convergence in Technology, I2CT 2017. pp. 222–229. https://doi.org/10.1109/I2CT.2017.8226125

Chan, V.C.H., Beaudette, S.M., Smale, K.B., Beange, K.H.E., Graham, R.B., 2020. A subject-specific approach to detect fatigue-related changes in spine motion using wearable sensors. Sensors (Switzerland) 20. https://doi.org/10.3390/s20092646

Chen, W., Zhuang, J., Yu, W., Wang, Z., 2009. Measuring complexity using FuzzyEn, ApEn, and SampEn. Med Eng Phys 31, 61–68. https://doi.org/10.1016/j.medengphy.2008.04.005

Cheng, A.J., Rice, C.L., 2005. Fatigue and recovery of power and isometric torque following isotonic knee extensions. J Appl Physiol 99, 1446–1452. https://doi.org/10.1152/japplphysiol.00452.2005

Cholewicki, J., McGill, S., 1996. Mechanical stability of the in vivo lumbar spine: implications for injury and chronic low back pain. Clinical Biomechanics 11, 1–15. https://doi.org/10.1016/0268-0033(95)00035-6

Cifrek, M., Medved, V., Tonković, S., Ostojić, S., 2009. Surface EMG based muscle fatigue evaluation in biomechanics. Clinical Biomechanics 24, 327–340. https://doi.org/10.1016/j.clinbiomech.2009.01.010

Cohen, L., 1989. Time-frequency distributions-a review. Proceedings of the IEEE 77, 941–981. https://doi.org/10.1109/5.30749

Costa, M., Goldberger, A.L., Peng, C.K., 2002. Multiscale entropy analysis of complex physiologic time series. Phys Rev Lett 89, 6–9. https://doi.org/10.1103/PhysRevLett.89.068102

Da Costa, B.R., Vieira, E.R., 2010. Risk factors for work-related musculoskeletal disorders: A systematic review of recent longitudinal studies. Am J Ind Med 53, 285–323. https://doi.org/10.1002/ajim.20750

Darmawan, D., 2004. Electromyography, Journal of Chemical Information and Modeling. John Wiley & Sons, Inc., Hoboken, NJ, USA. https://doi.org/10.1002/0471678384

Day, S.J., Hulliger, M., 2001. Experimental simulation of cat electromyogram: evidence for algebraic summation of motor-unit action-potential trains. J Neurophysiol 86, 2144–2158. https://doi.org/10.1152/jn.2001.86.5.2144

De Luca, C.J., 1984. Myoelectrical manifestations of localized muscular fatigue in humans. Crit Rev Biomed Eng 11, 251–79.

De Luca, C.J., 1979. Physiology and Mathematics of Myoelectric Signals. IEEE Trans Biomed Eng BME-26, 313–325. https://doi.org/10.1109/TBME.1979.326534

Dempsey, P.G., 1998. A critical review of biomechanical, epidemiological, physiological and psychophysical criteria for designing manual materials handling tasks. Ergonomics 41, 73–88. https://doi.org/10.1080/001401398187332

Dimitrova, N.A., Dimitrov, G. V., 2003. Interpretation of EMG changes with fatigue: Facts, pitfalls, and fallacies. Journal of Electromyography and Kinesiology 13, 13–36. https://doi.org/10.1016/S1050-6411(02)00083-4

Dingwell, J.B., Marin, L.C., 2006. Kinematic variability and local dynamic stability of upper body motions when walking at different speeds. J Biomech 39, 444–452. https://doi.org/10.1016/j.jbiomech.2004.12.014

Ebenbichler, G.R., Bonato, P., Roy, S.H., Lehr, S., Posch, M., Kollmitzer, J., Della Croce, U., 2002. Reliability of EMG time-frequency measures of fatigue during repetitive lifting. Med Sci Sports Exerc 34, 1316–1323. https://doi.org/10.1097/00005768-200208000-00013

Ebenbichler, G.R., Unterlerchner, L., Habenicht, R., Bonato, P., Kollmitzer, J., Mair, P., Riegler, S., Kienbacher, T., 2017. Estimating neural control from concentric vs. eccentric surface electromyographic representations during fatiguing, cyclic submaximal back extension exercises. Front Physiol 8. https://doi.org/10.3389/fphys.2017.00299

Edwards, R.H., 1981. Human muscle function and fatigue. Ciba Found Symp 82, 1–18. https://doi.org/10.1002/9780470715420.ch1

Enoka, R.M., Baudry, S., Rudroff, T., Farina, D., Klass, M., Duchateau, J., 2011. Unraveling the neurophysiology of muscle fatigue. Journal of Electromyography and Kinesiology 21, 208–219. https://doi.org/10.1016/j.jelekin.2010.10.006

Everett, J.G., 1999. Overexertion injuries in construction. J Constr Eng Manag 125, 109–114. https://doi.org/10.1061/(asce)0733-9364(1999)125:2(109)

Fallentin, N., Jørgensen, K., Simonsen, E.B., 1993. Motor unit recruitment during prolonged isometric contractions. Eur J Appl Physiol Occup Physiol 67, 335–341. https://doi.org/10.1007/BF00357632

Farina, D., 2006. Interpretation of the surface electromyogram in dynamic contractions. Exerc Sport Sci Rev 34, 121–127. https://doi.org/10.1249/00003677-200607000-00006

Farina, D., Cescon, C., Merletti, R., 2002. Influence of anatomical, physical, and detection-system parameters on surface EMG. Biol Cybern 86, 445–456. https://doi.org/10.1007/s00422-002-0309-2

Farina, D., Merletti, R., Nazzaro, M., Caruso, I., 2001. Effect of joint angle on EMG variables in leg and thigh muscles. IEEE Engineering in Medicine and Biology Magazine 20, 62–71. https://doi.org/10.1109/51.982277

Gandevia, S.C., 2001. Spinal and supraspinal factors in human muscle fatigue. Physiol Rev 81, 1725–1789. https://doi.org/10.1152/physrev.2001.81.4.1725

Gandevia, S.C., Allen, G.M., Butler, J.E., Taylor, J.L., 1996. Supraspinal factors in human muscle fatigue: Evidence for suboptimal output from the motor cortex. Journal of Physiology 490, 529–536. https://doi.org/10.1113/jphysiol.1996.sp021164

Gates, D.H., Dingwell, J.B., 2010. Muscle fatigue does not lead to increased instability of upper extremity repetitive movements 43, 913–919. https://doi.org/10.1016/j.jbiomech.2009.11.001.Muscle

Goldberger, A.L., Amaral, L.A.N., Hausdorff, J.M., Ivanov, P.C., Peng, C.K., Stanley, H.E., 2002. Fractal dynamics in physiology: Alterations with disease and aging. Proc Natl Acad Sci U S A 99, 2466–2472. https://doi.org/10.1073/pnas.012579499

González-Izal, M., Malanda, A., Gorostiaga, E., Izquierdo, M., 2012. Electromyographic models to assess muscle fatigue. Journal of Electromyography and Kinesiology. https://doi.org/10.1016/j.jelekin.2012.02.019

González-Izal, M., Rodríguez-Carreño, I., Malanda, A., Mallor-Giménez, F., Navarro-Amézqueta, I., Gorostiaga, E.M., Izquierdo, M., 2010. sEMG wavelet-based indices predicts muscle power loss during dynamic contractions. Journal of Electromyography and Kinesiology 20, 1097–1106. https://doi.org/10.1016/j.jelekin.2010.05.010

Graham, R.B., Oikawa, L.Y., Ross, G.B., 2014. Comparing the local dynamic stability of trunk movements between varsity athletes with and without non-specific low back pain. J Biomech 47, 1459–1464. https://doi.org/10.1016/j.jbiomech.2014.01.033

Graham, R.B., Sadler, E.M., Stevenson, J.M., 2012. Local dynamic stability of trunk movements during the repetitive lifting of loads. Hum Mov Sci 31, 592–603. https://doi.org/10.1016/j.humov.2011.06.009

Graham, R.B., Wachowiak, M.P., Gurd, B.J., 2015. The assessment of muscular effort, fatigue, and physiological adaptation using EMG and wavelet analysis. PLoS One 10, 1–13. https://doi.org/10.1371/journal.pone.0135069

Granata, K.P., Gottipati, P., 2008. Fatigue influences the dynamic stability of the torso. Ergonomics 51, 1258–1271. https://doi.org/10.1080/00140130802030722

Grassberger, P., Procaccia, I., 1983. Estimation of the Kolmogorov entropy from a chaotic signal. Phys Rev A (Coll Park) 28, 2591–2593. https://doi.org/10.1103/PhysRevA.28.2591

Hernandez, L., Camic, C., 2019. Fatigue-Mediated loss of complexity is contraction-type dependent in vastus lateralis electromyographic signals. Sports 7, 78. https://doi.org/10.3390/sports7040078

Kahl, L., Hofmann, U.G., 2016. Comparison of algorithms to quantify muscle fatigue in upper limb muscles based on sEMG signals. Med Eng Phys 38, 1260–1269. https://doi.org/10.1016/j.medengphy.2016.09.009

Kajimoto, O., 2008. Development of a method of evaluation of fatigue and its economic impacts, Fatigue Science for Human Health. Springer Japan, Tokyo. https://doi.org/10.1007/978-4-431-73464-2

Karlsson, S., Gerdle, B., 2001. Mean frequency and signal amplitude of the surface EMG of the quadriceps muscles increase with increasing torque - A study using the continuous wavelet transform. Journal of Electromyography and Kinesiology 11, 131–140. https://doi.org/10.1016/S1050-6411(00)00046-8

Karlsson, S., Jun Yu, Akay, M., 2000. Time-frequency analysis of myoelectric signals during dynamic contractions: a comparative study. IEEE Trans Biomed Eng 47, 228–238. https://doi.org/10.1109/10.821766

Kent, J.A., Ørtenblad, N., Hogan, M.C., Poole, D.C., Musch, T.I., 2016. No muscle is an Island: Integrative perspectives on muscle fatigue. Med Sci Sports Exerc 48, 2281–2293. https://doi.org/10.1249/MSS.0000000000001052

Kent-Braun, J.A., Fitts, R.H., Christie, A., 2012. Skeletal muscle fatigue, in: Comprehensive Physiology. Wiley, pp. 997–1044. https://doi.org/10.1002/cphy.c110029

Khazan, I.Z., 2013. Surface Electromyography, in: The Clinical Handbook of Biofeedback. Wiley, pp. 118–156. https://doi.org/10.1002/9781118485309.ch10

Knaflitz, M., Bonato, P., 1999. Time-frequency methods applied to muscle fatigue assessment during dynamic contractions. Journal of Electromyography and Kinesiology 9, 337–350. https://doi.org/10.1016/S1050-6411(99)00009-7

Komi, P. V., Tesch, P., 1979. EMG frequency spectrum, muscle structure, and fatigue during dynamic contractions in man. Eur J Appl Physiol Occup Physiol 42, 41–50. https://doi.org/10.1007/BF00421103

Komi, P. v., Viitasalo, J.H.T., 1976. Signal characteristics of EMG at different levels of muscle tension. Acta Physiol Scand 96, 267–276. https://doi.org/10.1111/j.1748-1716.1976.tb10195.x

Kumar, S., 2001. Theories of musculoskeletal injury causation. Ergonomics 44, 17–47. https://doi.org/10.1080/00140130120716

Kumar, S., 1990. Cumulative load as a risk factor for back pain. Spine (Phila Pa 1976). https://doi.org/10.1097/00007632-199012000-00014

Lee, K.A., Hicks, G., Nino-Murcia, G., 1991. Validity and reliability of a scale to assess fatigue. Psychiatry Res 36, 291–298. https://doi.org/10.1016/0165-1781(91)90027-M

Liao, F., Zhang, X., Cao, C., Hung, I.Y.J., Chen, Y., Jan, Y.K., 2021. Effects of muscle fatigue and recovery on complexity of surface electromyography of biceps brachii. Entropy 23. https://doi.org/10.3390/e23081036

Lin, S.Y., Hung, C.I., Wang, H.I., Wu, Y. Te, Wang, P.S., 2016. Extraction of physically fatigue feature in exercise using electromyography, electroencephalography and electrocardiography, in: Proceedings - International Conference on Natural Computation. pp. 561–566. https://doi.org/10.1109/ICNC.2015.7378050

Mahdavi, N., Motamedzade, M., Jamshidi, A.A., Darvishi, E., Moghimbeygi, A., Moghadam, R.H., 2018. Upper trapezius fatigue in carpet weaving: The impact of a repetitive task cycle. International Journal of Occupational Safety and Ergonomics 24, 41–51. https://doi.org/10.1080/10803548.2016.1234706

Merletti, R., Knaflitz, M., De Luca, C.J., 1990. Myoelectric manifestations of fatigue in voluntary and electrically elicited contractions. J Appl Physiol 69, 1810–1820. https://doi.org/10.1152/jappl.1990.69.5.1810

Merletti, R., Rainoldi, A., Farina, D., 2004. Myoelectric manifestations of muscle fatigue, in: Electromyography. John Wiley & Sons, Inc., Hoboken, NJ, USA, pp. 233–258. https://doi.org/10.1002/0471678384.ch9

Mesin, L., Merletti, R., Rainoldi, A., 2009. Surface EMG: The issue of electrode location. Journal of Electromyography and Kinesiology 19, 719–726. https://doi.org/10.1016/j.jelekin.2008.07.006

Missenard, O., Mottet, D., Perrey, S., 2008. The role of cocontraction in the impairment of movement accuracy with fatigue. Exp Brain Res 185, 151–156. https://doi.org/10.1007/s00221-007-1264-x

Mital, A., Foononi-Fard, H., Brown, M.L., 1994. Physical fatigue in high and very high frequency manual materials handling: Perceived exertion and physiological indicators. Hum Factors 36, 219–231. https://doi.org/10.1177/001872089403600204

Monjo, F., Terrier, R., Forestier, N., 2015. Muscle fatigue as an investigative tool in motor control: A review with new insights on internal models and posture-movement coordination. Hum Mov Sci 44, 225–233. https://doi.org/10.1016/j.humov.2015.09.006

Navaneethakrishna, M., Karthick, P.A., Ramakrishnan, S., 2015. Analysis of biceps brachii sEMG signal using multiscale fuzzy approximate entropy. Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS 2015-Novem, 7881–7884. https://doi.org/10.1109/EMBC.2015.7320219

Nieminen, H., Takala, E.P., 1996. Evidence of deterministic chaos in the myoelectric signal. Electromyogr Clin Neurophysiol 36, 49–58.

Nussbaum, M.A., 2001. Static and dynamic myoelectric measures of shoulder muscle fatigue during intermittent dynamic exertions of low to moderate intensity. Eur J Appl Physiol 85, 299–309. https://doi.org/10.1007/s004210100454

Otsu, N., Smith, P.L., Reid, D.B., Environment, C., Palo, L., Alto, P., Smith, P.L., 1979. Otsu_1979_otsu_method. IEEE Trans Syst Man Cybern C, 62–66.

Paillard, T., 2012. Effects of general and local fatigue on postural control: A review. Neurosci Biobehav Rev 36, 162–176. https://doi.org/10.1016/j.neubiorev.2011.05.009

Parijat, P., Lockhart, T.E., 2008. Effects of lower extremity muscle fatigue on the outcomes of slip-induced falls. Ergonomics 51, 1873–1884. https://doi.org/10.1080/00140130802567087

Pethick, J., Winter, S.L., Burnley, M., 2019. Fatigue reduces the complexity of knee extensor torque during fatiguing sustained isometric contractions. Eur J Sport Sci 19, 1349–1358. https://doi.org/10.1080/17461391.2019.1599450

Pincus, S.M., 1991. Approximate entropy as a measure of system complexity. Proceedings of the National Academy of Sciences 88, 2297–2301. https://doi.org/10.1073/pnas.88.6.2297

Piper, H., 1912. Elektrophysiologie menschlicher Muskeln, Elektrophysiologie menschlicher Muskeln. Springer Berlin Heidelberg, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-50944-5

Potvin, J.R., Bent, L.R., 1997. A validation of techniques using surface EMG signals from dynamic contractions to quantify muscle fatigue during repetitive tasks. Journal of Electromyography and Kinesiology 7, 131–139. https://doi.org/10.1016/S1050-6411(96)00025-9

Preatoni, E., Hamill, J., Harrison, A.J., Hayes, K., van Emmerik, R.E.A., Wilson, C., Rodano, R., 2013. Movement variability and skills monitoring in sports. Sports Biomech 12, 69–92. https://doi.org/10.1080/14763141.2012.738700

Radwin, R.G., Marras, W.S., Lavender, S.A., 2001. Biomechanical aspects of work-related musculoskeletal disorders, Theoretical Issues in Ergonomics Science. https://doi.org/10.1080/14639220110102044

Rampichini, S., Vieira, T.M., Castiglioni, Merati, G., 2020. Complexity analysis of surface electromyography for assessing the myoelectric manifestation of muscle fatigue: A review. *Entropy* 2022, 22, 529. https://doi.org/10.3390/E22050529

Richman, J.S., Moorman, J.R., 2000. Physiological time-series analysis using approximate entropy and sample entropy maturity in premature infants Physiological time-series analysis using approximate entropy and sample entropy. Americal Journal of Physiology Heart and Circulatory Physiology 278, H2039–H2049.

Roberto, M., Philip J., P., 2004. Electromyography: Physiology, Engineering, and Noninvasive Applications, IEEE Engineering in Medicine and Biology Magazine. Wiley-IEEE Press. https://doi.org/10.1109/emb-m.2006.250500

Robertson, D.G.E., Caldwell, G.E., Hamill, J., Kamen, G., Whittlesey, S.N., 2014. Research methods in biomechanics, Research Methods in Biomechanics. https://doi.org/10.5040/9781492595809

Rogers, D.R., MacIsaac, D.T., 2013. A comparison of EMG-based muscle fatigue assessments during dynamic contractions. Journal of Electromyography and Kinesiology 23, 1004–1011. https://doi.org/10.1016/j.jelekin.2013.05.005

Roquelaure, Y., Ha, C., Leclerc, A., Touranchet, A., Sauteron, M., Melchior, M., Imbernon, E., Goldberg, M., 2006. Epidemiologic surveillance of upper-extremity musculoskeletal disorders in the working population. Arthritis Care Res (Hoboken) 55, 765–778. https://doi.org/10.1002/art.22222

Ross, G.B., Mavor, M., Brown, S.H.M., Graham, R.B., 2015. The Effects of Experimentally Induced Low Back Pain on Spine Rotational Stiffness and Local Dynamic Stability. Ann Biomed Eng 43, 2120–2130. https://doi.org/10.1007/s10439-015-1268-9

Roy, S.H., Bonato, P., Knaflitz, M., 1998. EMG assessment of back muscle function during cyclical lifting. Journal of Electromyography and Kinesiology 8, 233–245. https://doi.org/10.1016/S1050-6411(98)00010-8

Søgaard, K., Gandevia, S.C., Todd, G., Petersen, N.T., Taylor, J.L., 2006. The effect of sustained low-intensity contractions on supraspinal fatigue in human elbow flexor muscles. Journal of Physiology 573, 511–523. https://doi.org/10.1113/jphysiol.2005.103598

Song, M., Segala, D.B., Dingwell, J.B., Chelidze, D., 2009. Slow-time changes in human EMG muscle fatigue states are fully represented in movement kinematics. J Biomech Eng 131, 1–11. https://doi.org/10.1115/1.3005177

Sparto, P.J., Parnianpour, M., Reinsel, T.E., Simon, S., 1997. The effect of fatigue on multijoint kinematics, coordination, and postural stability during a repetitive lifting test. Journal of Orthopaedic and Sports Physical Therapy 25, 3–12. https://doi.org/10.2519/jospt.1997.25.1.3

Sung, P.S., Zurcher, U., Kaufman, M., 2010. Reliability difference between spectral and entropic measures of erector spinae muscle fatigability. Journal of Electromyography and Kinesiology 20, 25–30. https://doi.org/10.1016/j.jelekin.2008.11.005

Sung, P.S., Zurcher, U., Kaufman, M., 2007. Comparison of spectral and entropic measures for surface electromyography time series: A pilot study. J Rehabil Res Dev 44, 599–609. https://doi.org/10.1682/JRRD.2006.10.0132

Tang, K.H.D., 2022. The prevalence, causes and prevention of occupational musculoskeletal disorders. Global Academic Journal of Medical Sciences 4, 56–68. https://doi.org/10.36348/gajms.2022.v04i02.004

Tong, H., Zhang, X., Ma, H., Chen, Y., Chen, X., 2016. Fatiguing effects on the multi-scale entropy of surface electromyography in children with cerebral palsy. Entropy 18. https://doi.org/10.3390/e18050177

Troiano, A., Naddeo, F., Sosso, E., Camarota, G., Merletti, R., Mesin, L., 2008. Assessment of force and fatigue in isometric contractions of the upper trapezius muscle by surface EMG signal and perceived exertion scale. Gait Posture 28, 179–186. https://doi.org/10.1016/j.gaitpost.2008.04.002

Uchida, T., Delp, S.L., 2021. Biomechanics of Movement: The Science of Sports, Robotics, and Rehabilitation. MIT Press.

Vaillancourt, D.E., Newell, K.M., 2002. Changing complexity in human behavior and physiology through aging and disease. Neurobiol Aging 23, 1–11. https://doi.org/10.1016/S0197-4580(01)00247-0

Vigotsky, A.D., Halperin, I., Lehman, G.J., Trajano, G.S., Vieira, T.M., 2018. Interpreting signal amplitudes in surface electromyography studies in sport and rehabilitation sciences. Front Physiol 8. https://doi.org/10.3389/fphys.2017.00985

Vøllestad, N.K., 1997. Measurement of human muscle fatigue. J Neurosci Methods 74, 219–227. https://doi.org/10.1016/S0165-0270(97)02251-6

Warburton, D.E.R., Jamnik, V.K., Bredin, S.S.D., Gledhill, N., 2011. The physical activity readiness questionnaire for everyone (PAR-Q+) and electronic physical activity readiness medical examination (ePARmed-X+). The Health & Fitness Journal of Canada 4, 3–23. https://doi.org/10.14288/HFJC.V4I2.103

Westerblad, H., Allen, D.G., Bruton, J.D., Andrade, F.H., Lännergren, J., 1998. Mechanisms underlying the reduction of isometric force in skeletal muscle fatigue. Acta Physiol Scand 162, 253–60. https://doi.org/10.1046/j.1365-201X.1998.0301f.x

Westgaard, R.H., De Luca, C.J., 1999. Motor unit substitution in long-duration contractions of the human trapezius muscle. J Neurophysiol 82, 501–504. https://doi.org/10.1152/jn.1999.82.1.501

Williams, C.A., Ratel, S., 2009. Human muscle fatigue, Human Muscle Fatigue. https://doi.org/10.4324/9780203885482

Williamson, A., Friswell, R., 2013. Fatigue in the workplace: causes and countermeasures. Fatigue 1, 81–98. https://doi.org/10.1080/21641846.2012.744581

Xie, H.-B., Guo, J.-Y., Zheng, Y.-P., 2010. Fuzzy approximate entropy analysis of chaotic and natural complex systems: Detecting muscle fatigue using electromyography signals. Ann Biomed Eng 38, 1483–1496. https://doi.org/10.1007/s10439-010-9933-5

Yaggie, J.A., McGregor, S.J., 2002. Effects of isokinetic ankle fatigue on the maintenance of balance and postural limits. Arch Phys Med Rehabil 83, 224–228. https://doi.org/10.1053/apmr.2002.28032

Yin, P., Yang, L., Wang, C., Qu, S., 2019. Effects of wearable power assist device on low back fatigue during repetitive lifting tasks. Clinical Biomechanics 70, 59–65. https://doi.org/10.1016/j.clinbiomech.2019.07.023

Yung, M., Wells, R., 2016. How do we measure neuromuscular fatigue at the workplace? Center of Research Expertise for the Prevention of Musculoskeletal Disorders 4164–8. https://doi.org/10.1080/00140139.2014.934299.Position.

Zhu, W., Vader, A.M., Chadda, A., Leu, M.C., Liu, X.F., Vance, J.B., 2013. Wii remote-based low-cost motion capture for automated assembly simulation. Virtual Real 17, 125–136. https://doi.org/10.1007/s10055-011-0204-z

Zhu, X., Zhang, X., Tang, X., Gao, X., Chen, X., 2017. Re-evaluating electromyogram-force relation in healthy biceps brachii muscles using complexity measures. Entropy 19, 5–7. https://doi.org/10.3390/e19110624

Zipp, P., 1982. Recommendations for the standardization of lead positions in surface electromyography. Eur J Appl Physiol Occup Physiol 50, 41–54. https://doi.org/10.1007/BF00952243

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Faculty of Health Sciences

School of Human Kinetics

Appendix A

Research Consent Form

Research Project Title: **Development of an IMU-driven task identification and fatigue prediction framework (Preliminary Study)**

Principal Investigator:

Student Researchers:

COVID-19 Precautions

For the safety of both yourself and the researchers, precautions have been put in place to try and prevent the spread of COVID-19. Before arriving at the lab, you and the researchers will be screened for COVID-19 symptoms and will be asked to use hand sanitizer upon entering and exiting the lab. Both you and the researchers are required to wear a mask at all times during the data collection. All equipment that is touched by either a participant or researcher during the collection will be sanitized using disinfectant before and after the collection and all washable materials will be washed prior to each participants' session.

Background and Purpose of the Study

Fatigue in the workplace is associated with an increased risk for the occurrence of occupational accidents and the development of musculoskeletal disorders (MSDs). Typical fatigue assessment methods can detract individuals from the performance of their task (e.g., subjective perception scales, strength tests, etc.). Unobtrusively recognizing when workers may be excessively fatigued can provide data to encourage timely breaks, optimize work-rest ratios, and inform job rotation

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schedules, all of which can mitigate the risk for accidents and MSDs. If the most relevant movement and muscle activation variables can be identified, then machine learning-based models can be developed to automatically estimate fatigue levels.

Thus, the purpose of this study is to use movement data and fatigue measurements to develop machine learning-based models capable of estimating fatigue levels. To accomplish this, movement and muscle activation variables associated with fatigue status during dynamic, simulated manual handling tasks need to be identified. During repetitive spine flexion-extension (FE) movements, your trunk and shoulder muscle activation, heart rate, and upper-body movement will be measured using surface electromyography (EMG), a heart rate monitor, and wearable inertial measurement units (IMUs), respectively.

Description of Study Procedures

You are invited to participate in a one-day motion analysis procedure for approximately 2 hours at the University of Ottawa Human Movement Biomechanics Laboratory (200 Lees Avenue, E020). The protocol consists of the performance of 13 sets of repetitive spine FE movements, where each set is comprised of 50 spine FE movements. You will be asked to perform one baseline set followed by an eight-minute rest. Then, you will be asked to perform 12 more sets of spine FE movements with no rest between sets. Immediately after each set (including baseline), your trunk muscle fatigue will be assessed using two methods: a self-report of your perceived fatigue, and a maximal isometric lift strength assessment. The self-report requires you to mark your fatigue on a scale, and the lift strength assessment requires you to pull upwards on a load cell with maximal force, 3 consecutive times. You will be constrained at the hip and instructed to keep your legs straight while extending your spine to "ramp up" the amount of force you exert. You will be asked to complete all FE sets and fatigue assessments unless your maximal lift strength becomes < 70% of your baseline value, or you become too fatigued to continue and wish to stop.

You will be asked to bring shoes and shorts that you are comfortable performing repetitive tasks in. Upon arrival, your height, mass, and various body measurements (e.g., shoulder height, arm length) will be measured. Then, you will be prepared to wear 7 EMG electrodes on the right side of your body, which includes sanitizing the attachment sites with alcohol wipes, and shaving to improve the electrode-skin interface (if necessary). The EMG electrodes will then be attached using medical-grade adhesive to your abdomen (external oblique), back (thoracic erector spinae, lumbar erector spinae, and latissimus dorsi on both sides), and shoulder (anterior and posterior deltoid). To normalize the readings from the EMG sensors, you will perform three trials of maximal voluntary contractions, comprised of a series of static pulling, sit-ups, and back extensions with your maximum strength. Once completed, a Samsung Galaxy Watch 4 will be worn on your left wrist to monitor heart rate. Lastly, you will be outfitted with the inertial motion capture suit. Using provided sanitized neoprene bands and a custom shirt, IMUs will be placed on your upper limbs, pelvis, and head. To calibrate the IMU system, you will be asked to stand in a neutral posture (N-pose), walk for 5 seconds forward, turn around, and return to an N-pose at the starting location. After these calibration trials are completed, the experimental trials will begin.

Data Analysis

The data collected will be analysed in two graduate students' projects: a master's engineering student (Di Kang) and a doctoral human kinetics candidate (Victor Chan). Complexity analysis of the EMG signals (e.g., sample entropy, a commonly-used measure of the irregularity of time-series signals) will be performed to determine their association with fatigue status during repetitive spine FE movements. The association between movement, EMG metrics, and fatigue status will be analysed, and the best metrics will be used in future research to develop machine learning-based models.

Possible Risks and Discomforts
Fatigue may occur through this protocol due to the performance of repetitive spine FE movements. However, any risk to you will be minimized by allowing you to stop at any point during the data collection. To do so, you can simply say "I wish to stop" or something alike. Furthermore, you must indicate that you are willing and capable of experiencing physical fatigue prior to participating. Shaving may be necessary to improve the contact between the EMG electrodes and skin; this may cause minor skin irritation. The tape used to attach the EMG electrodes may also cause minor skin irritation; similar to what is experienced with a bandage and typically fades within 2 to 3 days. 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 obtain any direct benefits from participating in this study, aside from a) performing fatiguing physical activity, and b) obtaining an educational opportunity to observe your own movement and muscle activation data on Xsens MVN Link software. However, the data collected will contribute to the development of machine learning-based models to estimate fatigue levels, which can help reduce MSD risk. Futhermore, the results of this study will contribute to the body of knowledge surrounding EMG analysis of fatigue during dynamic contractions.

Voluntary Participation
Twelve male or female participants aged 16 years of age or older will be recruited for this study on a first come, first served basis. Participants must be pain- and injury-free in the past 12 months and be cleared to participate in fatiguing, physical activity. If the necessary number of participants has been met, you will be informed by a researcher via email that the study has completed. Your participation is voluntary and thus, you have no obligation to participate in this study. You may withdraw from the study at any time before or during the data collection session with no penalty or coercion. If chose to withdaw, all your data will be destroyed.

Confidentiality
All personal information is kept confidential. Information gained from this study will be stored electronically and will need a password to access, which will only be known to Dr. Ryan Graham and the research team. Paper study records are stored in a locked cabinet in a locked office and will be destroyed after 5 years post-publication; electronic records without personally identifying information will be stored indefinitely. You will not be identified by name in any reports/presentations of the completed study, and your face will never be presented in any reports/presentations. Your anonymity will be strictly maintained – you will never be identified by name; only by an independent study number (e.g., S01).

Compensation
Compensation is not provided for your participation in this study.

Funding Source
This study is funded by the Natural Sciences and Engineering Research Council of Canada (NSERC; 153648)

Questions about the Study
You are free to ask questions at any time during the protocol and by contacting the investigators (on page 1). The ethical components of this research project have been approved by the University of Ottawa research ethics board. If you have any questions regarding the ethical conduct of this study, please contact:

Protocol Officer for Ethics in Research at the University of Ottawa
Tabaret Hall
550 Cumberland Street, Room 154
Ottawa ON, K1N 6N5
Tel.: (613) 562-5387
Email: ethics@uottawa.ca

There are two copies of the consent form, one of which is yours to keep.

Research Project Title: **Development of an IMU-driven task identification and fatigue prediction framework (Preliminary Study)**

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 Videos Taken

I consent to have video footage taken during the protocol. I understand that these videos are being used as part of the analysis and if any of these videos are used in a subsequent presentation or publication, that my face and any other identifiers will be blurred. You cannot participate in the research study without consenting to having video footage 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).
- ☐

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Formulaire de consentement à la recherche

Titre du projet de recherche: **Development of an IMU-driven task identification and fatigue prediction framework (Étude Préliminaire)**

Chercheur principal:

Étudiant-chercheur :

Précautions pour la COVID-19

Pour votre sécurité et la sécurité des chercheurs, des précautions ont été mises en place afin d'essayer de prévenir la propagation de la COVID-19. Avant d'arriver au laboratoire, les chercheurs et vous allez être filtrer pour des symptômes de COVID-19 et allez être demander d'utiliser du désinfectant pour les mains lorsque vous arrivez et partez du laboratoire. Les chercheurs et vous-même êtes requis de porter un masque en tout temps lors de la collection de données. Tout équipement qui sera touché par soit le participant ou le chercheur lors de la collection sera essuyer avec du désinfectant avant et après la collection de données et tout matériel nettoyable sera lavé entre chaque participant.

Contexte et objectif de l'étude

La fatigue au travail est liée à un risque accru d'occurrence de d'accidents au travail et de développement de troubles musculosquelettiques (TMS). Les méthodes d'évaluation typiques pour la fatigue peuvent détourner les individus de la performance de leur tâches (ex : les échelles de perception subjective, les tests de force, etc.). Être

capable de reconnaître quand les travailleurs sont excessivement fatigués de façon non-encombrante peut fournir des données qui encouragerons les pauses, l'optimisation des ratios travail-repos, et pour informer les horaires de rotation des tâches, ce qui peut atténuer les risques d'accidents et de TMS. Si les variables de mouvements et d'activation musculaire les plus pertinentes peuvent être identifiés, des modèles d'apprentissage automatique peuvent être développé pour automatiquement estimer les niveaux de fatigue des travailleurs.

Ainsi, l'objectif de cette étude est d'utiliser des données de mouvements et des mesures de fatigue pour développer des modèles basés sur l'apprentissage automatique capables d'estimer les niveaux de fatigues des travailleurs. Pour ce faire, les variables de mouvement et d'activation musculaire associées à l'état de fatigue lors de tâches de maniement manuelle simulées doivent être identifié. Pendant les mouvements répétitifs de flexion-extension (FE) de la colonne vertébrale, l'activation des muscles du tronc et des épaules, la fréquence cardiaque et les mouvements du haut du corps seront mesurés à l'aide d'une électromyographie de surface (EMG), d'un moniteur de fréquence cardiaque et d'unités de mesure inertielles portables (IMU), respectivement.

Description des procédures d'étude
Vous êtes invité à participer à une procédure d'analyse de mouvement sur de un jour qui durera a peu près une trois heures au Laboratoire de biomécanique du mouvement humain de l'Université d'Ottawa (200, avenue Lees, E020). Le protocol consiste de complêter 11 séries de mouvements répétitifs de FE de la colonne vertébrale, ou chaque séries est composé de 50 mouvements de FE de la colonne vertébrale. Il vous sera demandé de complêter une série qui agira comme base suivi de huit minutes de repos. Après, vous allez être demandé de complêter 10 séries supplémentaires de mouvements de FE de la colonne vertébrale sans arrêts entre les séries. Immédiatement après les séries (incluant celle de base), la fatigue de vos muscles du tronc sera évaluée à l'aide de deux méthodes : une auto-évaluation de votre fatigue perçue et une évaluation de votre force de levage isométrique maximale. L'auto-évaluation vous demande de marquer votre fatigue sur une échelle, et l'évaluation de la force de levage vous demande de tirer vers le haut sur une cellule de charge avec une force maximale trois fois consécutivement. Vous serez attachez au niveau des hanches et recevrez comme instruction de guarder vos jambes droites tout en étendant votre colonne vertébrale pour « augmenter » la quantité de force que vous produisez. Il vous sera demandé de complêter toutes les séries de FE et les évaluation de fatigue à moins que votre force maximale de levage descend sous 70% de votre valeure de base, ou vous devenez trop fatiguer pour continuer et souhaitez arrêter.

Nous vous demandons d'amener des souliers et des shorts dans lesquels vous êtes confortables de performer des tâches répétitives. À votre arrivé, votre taille et masse seront mesurés ainsi que plusieurs mesures corporelles (e.g., hauteur des épaules, longueur des bras). Alors, votre corps sera préparé pour porter 7 électrodes EMG sur le côté droit de votre corps, ce qui inclus désinfecter l'emplacement de l'électrode avec des lingettes alcoolisés et rasé la peau pour améliorer l'interaction peau-électrode (si nécessaire). Les électrodes seront par la suite placées sur la peau avec un adhésif de qualité médicale à votre abdomen (oblique externe), dos (redresseur thoracique, érecteur lombaire et grand dorsal des deux côtés) et votre épaule (deltoïde antérieur et postérieur). Pour normaliser vos données d'EMG, vous allez compléter trois essais de contractions volontaires maximales, comprenant une série de tirage statique, de redressements assis et d'extensions du dos avec votre force maximale. Une fois complété, une montre intelligente Samsung Galaxy Watch 4

sera porté sur votre poignet gauche pour surveiller la fréquence cardiaque. Finalement, vous allez porter un costume de capture de mouvements inertiels. En utilisant des bandes de néoprènes et un chandail individualisé désinfecté, des IMUs seront placés sur vos membres inférieures, membres supérieures, torse, pelvis, et tête. Pour calibrer le système d'IMUs, vous allez devoir vous tenir en posture neutre (N-pose), marcher vers l'avant pour cinq secondes, vous retourner, et retourner à la position neutre au point de départ. Une fois ces procédures de calibrations compléter, les essais expérimentaux peuvent commencer.

Analyse de données
Les données collectées seront analysées dans deux projets d'étudiants aux études supérieures : une étudiante en maîtrise d'ingénierie (Di Kang) et un candidat au doctorat dans les sciences de l'activité physique (Victor Chan). Des analyses de complexité des signaux d'EMG (e.g., l'entropie de l'échantillon, une mesure couramment utilisée pour l'irrégularité des signaux de séries chronologiques) seront compléter pour déterminer leur association avec le statu de fatigue pendant les tâches de mouvements de FE répétitives. L'association entre les mouvements, les données EMG, et le niveau de fatigue seront analysé, et les meilleurs métriques seront utilisées dans des recherches futures pour développer des modèles d'apprentissage automatique.

Risques possibles et inconforts
La fatigue peut s'accumuler pendant ce protocol en raison de la performance des tâches de maniement manuelle répétitives. Cependant, tout risques sera minimiser en vous permettant de vous arrêter à n'importe quel moment de la collection de données. Pour ce faire, il suffit de dire « Je souhaite arrêter », ou quelque chose à cet effet. De plus, vous devez indiquer si vous êtes prêt et capable de ressentir de la fatigue physique avant de participer. Le rasage peut être nécessaire pour améliorer le contacte entre la peau et les électrodes d'EMG; ce qui pourra causer de légères irritations. Le ruban adhésif utilisée pour attacher les électrodes d'EMG peut causer une légère irritation de la peau; similaire à ce qui est ressentis avec un bandage et disparaîtra généralement dans les 2 à 3 jours suivants. Si vous ressentez un inconfort majeur, veuillez-nous en informer immédiatement et demander des soins primaires auprès d'un professionnel de la santé sur le campus (100 Marie Curie, Ottawa, 613-664-3950) ou d'un professionnel de la santé de votre choix.

Avantages possibles
Vous ne bénéficierez pas directement de votre participation à cette étude autre que a) compléter de l'activité physique et b) obtenir une opportunité éducative d'observer vos propres mouvements et données d'activation musculaire dans le logiciel Esens MVN Link. Par contre, les données collectées vons contribuer au dévelopement de modèles d'apprentissage automatique pour estimer les niveuax de fatigues, ce qui aidera à réduire les risques de TMS. De surcroît, les résultats de cette étude vons contribuer au corps de savoir autour de l'analyse d'EMG sur la fatigue pendant des contractions musculaires dynamiques.

Participation volontaire
Douze participants hommes ou femmes âgés de 16 ans ou plus seront recrutés pour cette étude sur la base de premier arrivé premier servis. Les participants ne doivent pas avoir eu de douleur dans les 12 derniers mois et doivent être autorisé à participé dans de l'activité physique fatigante. Si le nombre nécessaire de participants est acquis, vous allez être informé par un des chercheurs par courriel que l'étude est complète. Vous n'êtes pas obligé de participer à cette étude; Votre

participation est volontaire. Vous pouvez également vous retirer de l'étude à n'importe quel moment, sans pénalité ni coercition. Si vous décider de vous retirer de l'étude, toutes vos données seront détruites.

Confidentialité
Toutes les informations personnelles sont gardées confidentielles. Les informations tirées de cette étude seront stockées électroniquement et nécessiteront un mot de passe pour y accéder, qui ne sera connu que par Dr. Ryan Graham et l'équipe de recherche. Les dossiers d'étude sur papier sont stockés dans une armoire verrouillée et seront détruits 5 ans après leur publication; les dossiers électroniques seront supprimés et les dossiers papier seront déchiquetés. Vous ne serez pas identifié par nom dans les rapports finaux de l'étude ou présentations et votre visage de sera jamais présenté dans les rapports/présentations. Votre anonymat sera strictement maintenu - vous ne serez pas identifié par votre nom, mais sera déterminé par un numéro d'étude indépendant (ex : S01).

Compensation
Vous ne recevrez aucune compensation pour votre participation dans cette étude.

Source de financement
Cette étude est financé par le Conseil de Recherche en Sciences Naturelles et en Génie de Canada (CRSNG ; 153648).

Questions sur l'étude
Vous êtes libre de poser des questions à tout moment pendant le protocole et en communiquant avec les chercheurs par courriel (sur la première page). Les composantes éthiques de ce projet de recherche ont été approuvées par le comité d'éthique de la recherche de l'Université d'Ottawa. Si vous avez des questions concernant la conduite éthique de cette étude, vous pouvez communiquer avec l'agente de protocole pour l'éthique de la recherche, Université d'Ottawa, Pavillon Tabaret, 550, rue Cumberland, pièce 154, Ottawa (Ontario) K1N 6N5. Tél .: (613) 562-5387 Courriel: ethics@uottawa.ca.

Il y a deux copies du formulaire de consentement, dont l'une est à vous de conserver.

Titre du projet de recherche: **Development of an IMU-driven task identification and fatigue prediction framework (Étude Préliminaire)**

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'investigateur (ou personne expliquant le consentement):
J'ai soigneusement expliqué au participant à la recherche la nature de l'étude de recherche ci-dessus. À ma connaissance, le participant à la recherche qui signe ce formulaire de consentement comprend la nature, les exigences, les risques et les avantages de participer à cette étude. Je reconnais ma responsabilité pour les soins et le bien-être du participant à la recherche ci-dessus, pour respecter les droits et les souhaits du participant à la recherche, et pour mener l'étude conformément aux directives et règlements applicables en matière de bonnes pratiques cliniques.

_____
Nom de l'enquêteur / délégué (imprimé)

_____ _____
Signature de l'enquêteur / délégué Date

Consentement pour la prise de photos:
Je consens à la prise de photos en complétant l'expérience, et je comprends qu'aucune photo ne sera prise à aucun moment sans que je le sache. Je comprends également que si l'une de ces images est utilisée dans une présentation ou une publication ultérieure, mon visage et tous les autres identifiants seront flous. Vous pouvez toujours participer à l'étude de recherche sans consentir à la prise de photos.

_____ _____
Nom Date

_____
Signature

_____ _____
Nom du témoin Signature du témoin

Participation future:

- ☐ Je suis intéressé à être contacté pour participer à de futures recherches effectuées par ce laboratoire (vos informations d'email seront sauvegardées dans un fichier protégé par mot de passe).
- ☐

Appendix B

Muscle Fatigue Study 2022

Sex:_____ Age:_____ Height:_____

"Baseline1" Strength & VAS: |----------|

"Baseline2" Strength

"Fatigue1" Strength & VAS: |----------|

"Fatigue2" Strength & VAS: |----------|

"Fatigue3" Strength & VAS: |----------|

"Fatigue4" Strength & VAS: |----------|

"Fatigue5" Strength & VAS: |----------|

"Fatigue6" Strength & VAS: |----------|

"Fatigue7" Strength & VAS: |----------|

"Fatigue8" Strength & VAS: |----------|

"Fatigue9" Strength & VAS: |----------|

"Fatigue10" Strength & VAS: |----------|

"Fatigue11" Strength & VAS: |----------|

"Fatigue12" Strength & VAS: |----------|

Appendix C

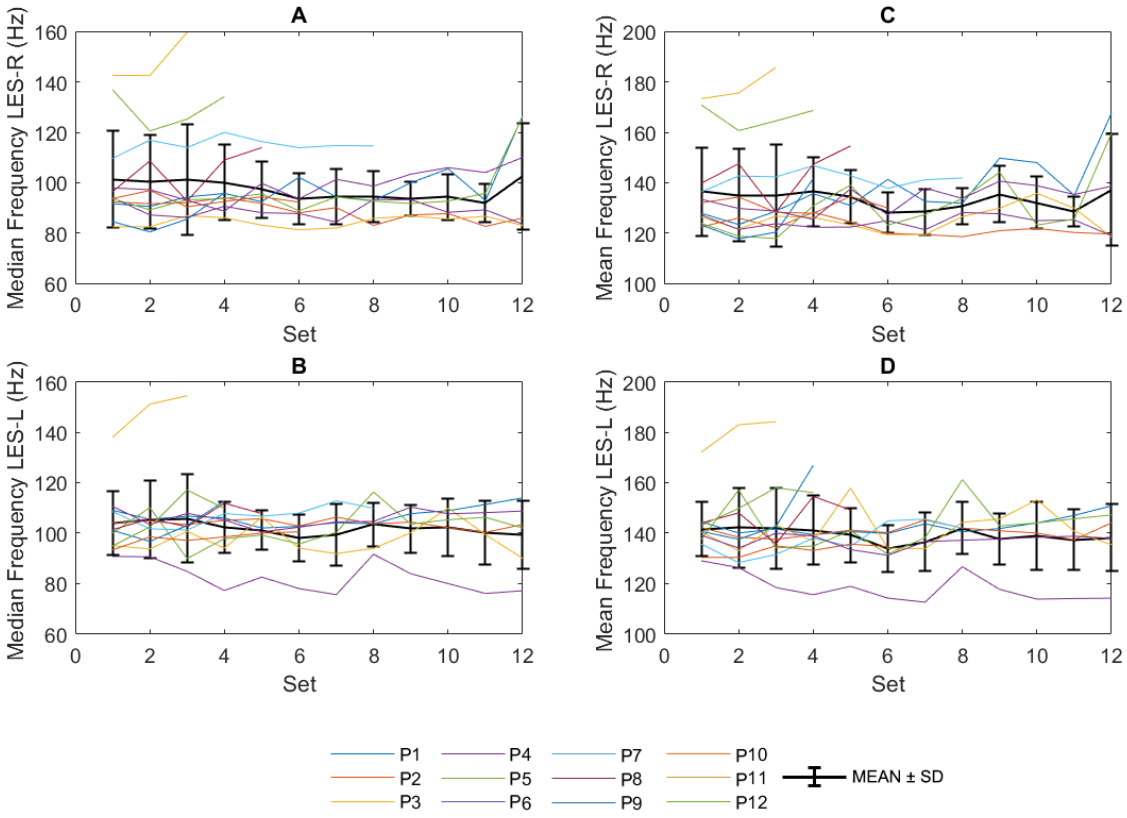

Figure C.1. The frequency components of the participants' left and right lumbar erector spinae during the maximum pulling strength tests after completing each set of repetitive trunk flexion-extension movements. (A) median frequency of right lumbar erector spinae (LES-R); (B) median frequency of left lumbar erector spinae (LES-L); (C) mean frequency of right lumbar erector spinae (LES-R); (D) mean frequency of left lumbar erector spinae (LES-L).

The median and mean frequency of the sEMG signal during the maximum pulling strength tests after completing each set of repetitive trunk flexion-extension movements are presented in Figure C.1. Both metrics were calculated from the power spectrum of the sEMG signal using the Fourier Transform, for the sEMG signal during isometric pulling movement could be considered as a stationary signal. Overall, no visible change was observed in both sEMG metrics, suggesting that lumbar back muscles may not be the dominant muscle during the pulling task for many participants.