Jerk as a Method of Identifying Physical Fatigue and Skill Level in Construction Work

by

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AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Researchers have shown that physically demanding work, characterized by forceful exertions, repetition, and prolonged duration can result in fatigue. Physical fatigue has been identified as a risk factor for both acute and cumulative injuries. Thus, monitoring worker fatigue levels is highly important in health and safety programs as it supports proactive measures to prevent or reduce instances of injury to workers. Recent advancements in sensing technologies, including inertial measurement units (IMUs), present an opportunity for the real-time assessment of individuals' physical exposures. These sensors also exceed the ability of mature motion capture technologies to accurately provide fundamental parameters such as acceleration and its derivative, jerk.

Although jerk has been used for a variety of clinical application to assess motor control, it has seldom been studied for applications in physically-demanding occupations that are directly related to physical fatigue detection [1]. This research uses IMU-based motion tracking suits to evaluate the use of jerk to detect changes in motor control. Since fatigue degrades motor control, and thus motion smoothness, it is expected that jerk values will increase with fatigue. Jerk can be felt as the change in force on the body leading to biomechanical injuries over time. Although it is known that fatigue contributes to a decline in motor control, there are no explicit studies that show the relationship between jerk and fatigue. In addition, jerk as it relates to skill level of highly repetitive and demanding work has also remained unexplored. To examine these relationships, our first study evaluates: 1) the use of jerk to detect changes in motor control arising from physical exertion and 2) differences in jerk values between motions performed by workers with varying skill levels. Additionally, we conducted a second study to assess the suitability of machine learning techniques for automated physical fatigue monitoring.

Bricklaying experiments were conducted with participants recruited from the Ontario Brick and Stone Mason apprenticeship program. Participants were classified into four groups based on their level of masonry experience including novices, first-year apprentices, third-year apprentices, and journeymen who have greater than five years of experience. In our first study, jerk analysis was carried out on eleven body segments, namely the pelvis, and the dominant and non-dominant upper and lower limb segments. Our findings show that jerk values were consistently lowest for journeymen and highest for third-year apprentices across all eleven body segments. These findings suggest that the experience that journeymen gain over the course of their career improves their ability to perform

repetitive heavy lifts with smoother motions and greater control. Third-year apprentices performed lifts with the greatest jerk values, indicating poor motor performance. Attributed to this finding was the pressure that third-year apprentices felt to match their production levels to that of journeymen's, leading third-year apprentices to use jerkier, less controlled motions. Novices and first-year apprentices showed more caution towards risks of injury, moving with greater motor control, compared to the more experienced third-year apprentices. However, the production levels of novices and first-year apprentices falter far behind the production levels of other experience groups. Detectable increases between jerk values during the beginning (rested) and end (exerted) of the task were found only for the journeymen, which is attributed to their greater interpersonal similarities in learned technique and work pace.

In our second study, we investigated the use of support-vector machines (SVM) to automate the monitoring of physical exertion levels using jerk. The jerk values of the pelvis, upper arms, and thighs were used to classify inter-and intra-subject rested and exerted states. As expected, classification results demonstrated a significantly higher intra-subject rested/exerted classification than the inter-subject classification. On average, intra-subject classification achieved an accuracy of 94% for the wall building experiment and 80% for the first-course-of-masonry-units experiment.

The thesis findings lead us to conclude that: 1) jerk changes resulting from physical exertion and skill level can be assessed using IMUs, and 2) SVMs have the ability to automatically classify rested and exerted movements. The investigated jerk analysis holds promise for in-situ and real-time monitoring of physical exertion and fatigue which can help in reducing work-related injuries and illnesses.

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Chapter 1 Introduction

1.1 Overview

In the construction industry, tasks are often labor-intensive resulting in workers frequently suffering from muscle fatigue. Construction activities, which include repetitive lifting and handling of heavy loads, static work in awkward and prolonged postures, and exposure to vibrations and harsh weather conditions, have been known to cause work-related injuries and illnesses [2].

Among construction workers, musculoskeletal disorders (MSDs) are one of the most prevalent occupational health problems. MSDs are injuries and disorders of soft tissues including the muscles, tendons, ligaments, joints, cartilage, and the nervous system. Physical fatigue has been shown to result in increased risks of injury that lead to a variety of MSDs including lower back disorders, tendinitis, and carpal tunnel syndrome [3]. Construction workers and crews are highly prone to musculoskeletal injuries, because their daily tasks require them to use forceful exertions when lifting and carrying loads, bend and twist the back or limbs, and be exposed to vibrations or repetitive movements [4].

In Ontario, Canada, MSDs are the primary cause of lost-time work injury reported to the Workplace Safety and Insurance Board (WSIB). On a national level, the economic cost of MSDs is estimated to be $22 billion annually and is deemed to be the most costly medical condition in Canada [5]. The repercussions of MSDs cost Ontario workplaces hundreds of millions of dollars due to worker absence and lost productivity. Indirectly, employers face costs including overtime wages, training costs for replacement workers, and lost quality of work. In 2015, the rate of MSDs in construction was 16% higher than the rate of 29.8 per 10,000 full-time employees (FTEs) for all industries combined. Furthermore, the rate of injuries from overexertion in lifting was 10.6 per 10,000 FTEs in construction, higher than the average of all industries [6]. In 2015, overexertion from lifting and lowering caused 30% of the MSDs among construction workers. Over time, these injuries may develop into chronic conditions, functional impairments, and permanent disabilities.

Muscular fatigue is commonly believed to be a prominent risk factor for musculoskeletal disorders. Thus, this risk factor has introduced the need to monitor the degree of muscle fatigue in the field of ergonomics and physiological research. Several studies have developed and used various methods for fatigue assessment with the aim of reducing the extent of acute effects and to prevent long-term health outcomes.

However, since fatigue manifests itself in various ways, a single test to measure a single process among several complex interactions (e.g. biological and behavioral manifestations) might not be a representative method for fatigue detection. For instance, if a certain physiological function is heightened, it may only reflect the body's adaptive behavior instead of the degree of fatigue [7]. Thus, the fatigue quantification typically involves some combination of kinematics and kinetics, often supplemented or substituted by physiological (e.g. muscle activity or heart rate) and subjective (e.g. discomfort or exertion) measures.

While there is no single standard for fatigue measurement, there are numerous subjective and objective measurements techniques that have been adapted for occupational use [8]. However, several of these techniques are cumbersome and not practical on construction sites, highlighting a need for methods that can continuously monitor fatigue with minimal intrusion to construction activities.

Recent advances in wearable technologies present an opportunity for real-time and in situ assessment of fatigue development. One such technology is the inertial measurement unit (IMU). The capabilities of the IMU system allow for the study of a biomechanically-relevant metric, jerk.

1.2 Motivations

Accurate quantification of physical exposures is an important component of physical fatigue development. Improved instrumentation for data collection has been critical for occupational health and safety development. Assessment methods that rely on kinematic data are conventionally collected using camera-based systems which is the gold-standard for non-invasive body motion capture in research settings. However, these systems require expertise for use, extensive post-processing, and large installation spaces. They can also be restrictive of the natural movement of the wearer and thus unlikely to be adopted for on-site use. The advancement and increasing availability of wearable sensing technologies have made in situ monitoring and real-time assessment of individuals' physical exposures possible. As a result, these devices have become a popular device for monitoring physical activity in a work environment for the purpose of injury prevention [9][10].

While there has been an emphasis on research to develop occupational health and safety sensor systems and establish their potential in a lab environment [11], [12], most current workplace applications have been limited to 1) posture analysis [4], [13]–[15], 2) task classification [16], 3) physiological monitoring [17], [18], and 4) computerized application of traditional observational tools [19], and specialized fatigue applications. The specialized physical fatigue applications are limited to the following three domains: 1) athletics, where the focus is primarily on monitoring athletes' performances [20], [21], 2) sleep-induced fatigue, in mining [22], [23], and 3) driver drowsiness detection systems in transportation [24], [25], and 4) illness-related fatigue [26], [27]. However, in most physically-demanding occupations, e.g. construction, manufacturing, and agriculture, there have been minimal work-place applications using sensor systems that are directly related to physical fatigue detection [1].

1.3 Research Objectives

The primary objective of this thesis is to evaluate the suitability of using jerk as a measure of fatigue that is practical for in situ use such as a construction site. It is anticipated that its findings will provide insight for future research in fatigue detection. More specifically, this thesis will:

1. Evaluate the use of jerk to detect changes in motor control arising from physical exertion.
2. Investigate differences in jerk values between motions performed by workers with varying skill levels.
3. Assess the suitability of machine learning techniques for real-time physical fatigue monitoring.

To address these aims, this thesis is divided into two studies. In the masonry trade, the duties of bricklayers are physically intensive and highly repetitive. Thus, bricklaying was selected as the subject of focus in the two studies.

1.4 Research Approach

1.4.1 Study 1

The objective of our first study was to assess the feasibility of using jerk as an indicator of physical exertion as fatigue develops over the course of a demanding task. As a proof-of-concept, a pilot experiment was designed and conducted to test whether physical fatigue results in increased jerk values and whether the signal-to-noise ratio of jerk derived from IMU-based motion capture suits was high enough to detect it. Three participants were asked to perform a one-arm dumbbell row exercise in a bent-over position until the participants either reached exhaustion or until they could no longer keep a metronome pace. Jerk values during the first and last exercise sets were compared for each participant to detect differences between rested and exerted states.

On the premise of the initial validation of the hypothesis, we proceeded to conduct a study on indoor masonry work. The experiment was conducted at the Canadian Masonry Design Center (CMDC) indoor training facility in Mississauga, Ontario. Thirty-two male bricklayers with varying levels of masonry experience were recruited. Participants were grouped into four experience groups including 1) novices, 2) first-year apprentices, 3) third-year apprentices, and 4) journeymen. Participants were instructed to complete a pre-built lead wall (Figure 4(a)) using forty-five concrete masonry units (CMUs) each weighing 16.6 kg. Jerk analysis was carried out on eleven body segments, namely the pelvis, the dominant and non-dominant upper and lower limb segments. Two hypotheses were evaluated:

> **Hypothesis 1:** The novel fatigue measure, jerk can be used to detect changes in motor control arising from physical exertion.
>
> **Hypothesis 2:** Jerk can be used to differentiate between motions performed by workers with varying skill levels.

This study comes primarily from the following publications:

1. L. Zhang, M. M. Diraneyya, J. Ryu, C. T. Haas, and E. Abdel-Rahman, "Assessment of Jerk as an Indicator of Physical Exertion and Fatigue," tentatively accepted by *Automation in Construction*, 2019.
2. L. Zhang, M. M. Diraneyya, J. Ryu, C. T. Haas, and E. Abdel-Rahman, "Assessment of Jerk as a Method of Physical Fatigue Detection," in *Proceedings of the ASME 2018 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference - IDETC/CIE 2018*, 2018, pp. 1–6.

1.4.2 Study 2

In our first study, raw motion data required manual segmentation to ensure that jerk values were compared between the same action types. For example, the motion data collected during each lifting action (pick up – transport – lay down) were segmented out from other motions such as spreading mortar. However, manual segmentation of the data prevents applications for real-time assessments. This issue was addressed in our second study.

We conducted two sets of analysis: 1) we tested the feasibility of analyzing jerk values using continuous motion data collected from our previous study to monitor changes in motor control, and 2) we conducted a second experiment that evaluates changes in jerk values between two identical bricklaying tasks following a series of exhausting exercises. Continuously monitoring jerk is investigated in the present study using IMU sensors and SVMs, which have been used extensively to classify human motion patterns and activities. We also examine both the inter- and intra-subject differences of experienced workers. Six male bricklayers with an average of 22 years of masonry experience were recruited for the experiment. One hypothesis was evaluated:

Hypothesis 1: As rested and exerted states can create unique jerk signal patterns, machine learning algorithms using motion data can be used to monitor the development of physical exertion for real-time applications.

This study comes primarily from the following publication:

1. L. Zhang, M. M. Diraneyya, J. Ryu, C. T. Haas, and E. Abdel-Rahman, "Automated Monitoring of Physical Fatigue Using Jerk," in *Proceedings of the ISARC 2019 Automation and Robotics in Construction*, 2019.

1.5 Thesis Organization

First, a review of relevant literature on the definition of fatigue, current fatigue assessment methods, the relationship between jerk, to fatigue and skill level, and a background on motion capture systems will be presented (Chapter 2). Second, an exploratory study focused on evaluating jerk as a method for fatigue detection and evaluating skill level will be reported (Chapter 3). Third, machine learning techniques to enable real-time physical fatigue monitoring will be evaluated (Chapter 4). Finally, the knowledge acquired from the preceding studies will be summarized and future research directions will be presented (Chapter 5).

Chapter 2 Background and Literature Review

2.1 Physical Fatigue and Exertion

Fatigue is often an overlooked hazard on construction sites. Construction work involves significant physical and mental demands, however, physical fatigue is a critical short-term risk factor, since it can result in diminished motor control, reduced strength capacity, and reduced cognitive resources [28]–[30]. In the construction industry, workers are frequently exposed to heavy workloads, prolonged work schedules, and repetitive tasks, making physical fatigue inevitable. The effects of fatigue include increased injury risk, lowered productivity, and deficits in work quality [31], [32]. Physical fatigue can also result in the deterioration of health in the long term, including work-related musculoskeletal disorders (WMSD) [3], [9], chronic fatigue syndrome [32], and compromised immune function [33]. Physical fatigue has been shown to be a good indicator of injury risks [34]. Thus, fatigue detection and monitoring tools that allow for intervention prior to detrimental effects to workers' safety, health, and productivity are worth studying.

Fatigue is a universal symptom not only associated with most acute and chronic illnesses, but also with normal, healthy functioning and everyday life. The ubiquitous nature of fatigue, given the complex interaction of the biological processes, psychosocial phenomena, and behavioral manifestations involved, has made its understanding challenging for researchers and clinicians. Currently, there is no universally accepted standard for fatigue assessment due to several factors [1]. Some of these factors are as follows,

1. Fatigue development differs significantly between workplaces and occupation type.
2. A single mechanism is unlikely to explain fatigue under all conditions given the complexity of the human body.
3. The complex interactions between biological processes and psychosocial phenomena cannot be encompassed by a single definition.
4. Observed performance deterioration is unlikely explained by a single theory.

Historically, physical or muscle fatigue is defined as a decline in a muscle's ability to exert force as a result of performing a motor task [35]. For tasks that do not call for sustained exertion of maximal force, fatigue gradually develops over a period of time and results in a progressive decline in maximal force [36]. Construction tasks fall in this category, involving intermittent exertions of submaximal forces, which makes explicit evaluation of muscle fatigue cumbersome. In fact, muscles can continue to exert submaximal forces as they fatigue by marshaling more muscle fibers and more cognitive resources [30]. However, this is achieved at the cost of less regulated force levels as low frequency tremor sets in [37]. In addition, most construction tasks involve complex motion patterns and force exertions by multiple muscle groups. This occurrence not only increases the number of muscles concerned but also allows the body to compensate for muscle fatigue by recruiting different muscle groups and using different motion patterns, further complicating the process of fatigue assessment. The standard measure of muscle fatigue is a drop in motor unit firing rates recorded via electromyography [38]. In addition to being cumbersome, Li et al. [39] report that direct assessment of fatigue via surface electromyography (sEMG) is possible for superficial muscles in low fat areas but not for deep muscles, such as the lower back. Moreover, EMGs suffer from a low signal-to-noise ratio which further reduces its applicability [39]–[41]. Thus, it is more practical and relevant to worker ergonomics to quantify secondary metrics of "physical exertion", defined as a measure of overall fatigue in the muscle ensemble relevant to a task. This measure can then be used as an indicator that fatigue has reached levels that impact worker's safety, health, productivity or work quality.

2.2 Current Approaches to Fatigue Detection

The human body exhibits physical fatigue in several ways, thus researchers have developed a number of methods to measure fatigue [32]. These methods, however, are often limited in their applications, since they were by and large developed for specific contexts and objectives [42].

Numerous studies have been aimed at quantifying the degree of physical fatigue induced by various occupational tasks [31], [43], [44]. While there is no single standard measurement of fatigue, there are several subjective measurement scales and objective measurement techniques that have been adapted for occupational use. Early attempts at quantifying fatigue in an occupational setting involved subjective measurement scales, such as questionnaires and self-perceived exertion scales, that relied on subjective answers to a fixed set of questions relating to physical and mental fatigue [45]. Several construction related studies have continued to use subjective feedback scales and questionnaires for assessing fatigue or workload [28], [46]–[49]. However, due to the nature of fatigue perception, specific fatigue symptoms may differ among workers of different socio-cultural background or work conditions [8], [35]. Thus, subjective measurements of fatigue are usually tailored to the work environment and the target workforce [42]. Physiological measurements including heart rate, oxygen consumption, energy expenditure, and skin temperature are used to overcome the limitations of subjective measurements [31], [43], [50]. The downside to physiological measurements is that many factors can reduce their reliability including alcohol consumption, fitness level, and caffeine intake [110]. Analysis of surface electromyography (sEMG) signals is another widely used technique and considered the gold standard to assess and characterize muscle fatigue [41], [49], [51], [52]. SEMG signals are electrical signals generated from contracting skeletal muscles and are acquired using surface electrodes. During fatigue, signal characteristics vary either due to the inability of nerves to fire high-frequency motor unit action potentials to maintain the required force or chemical imbalances of metabolites in the muscle fiber. In Venugopal et al. [53], surface electromyography (sEMG) signals was used to differentiate between fatigue and non-fatigue conditions at the biceps brachii muscle. However, as mentioned earlier, studies have shown that sEMG is not suitable for deep muscles, such as the lower back and suffer from a low signal-to-noise ratio which reduces its applicability. Other methods used in practice include isometric strength tests, exercise endurance tests, muscle biopsy, and muscle imaging [54].

Since the aforementioned methods can be cumbersome or invasive, some researchers have attempted to detect physical fatigue non-invasively via secondary measures, such as increased physiological tremor, impairment of postural control, increased sway, and loss of multi-joint coordination [55]. These assessment methods rely on kinematic data collected optoelectronically, which is the gold-standard for non-invasive body motion capture in research settings [56], [57]. In practice, this method has limited use since it requires expertise, extensive post-processing, and large installation spaces [1]. Optoelectronic systems are also costly, cumbersome, and difficult to operate on most worksites [56].

Recent advances in wearable technologies present an opportunity for real-time and field-based assessment of fatigue. One such technology involves wearable inertial-measurement-unit (IMU) - based motion capture, which enables the automatic and continuous collection of whole-body motion data. IMUs integrate accelerometers, magnetometers and gyroscopes to measure acceleration, velocity, and orientation of body segments. Wearable IMUs are wireless, non-intrusive, versatile, and less costly compared to other methods of motion tracking and provide a plausible solution for body motion capture [10], [58]. Thus, they have high potential to be used as a field-based fatigue assessment method. Furthermore, their high-frequency sampling rates allow for the evaluation of a novel biomechanics metric: jerk.

A number of studies have attempted to assess the feasibility of using these methods to detect and monitor fatigue. Dieen et al. [59] used an optoelectronic system to investigate the effect of repetitive lifting on joint loading, joint coordination, and jerk. They found that joint loading and coordination did not change significantly over repetitive lifts, however jerk increased in all investigated lower back and lower extremity joints. This suggests that jerk may be sensitive enough to detect changes in motion patterns induced by fatigue as the body adapts to maintain torque, acceleration, and position profiles. Zhang et al. [60] used IMUs and support vector machines (SVM) to classify normal walking and post-fatigue walking. They found that features associated with acceleration and jerk of the lower extremities were significantly increased following a squat exercise. Maman et al. [61] assessed the feasibility of using penalized regression models for the detection and estimation of physical fatigue in simulated manufacturing tasks. Low-noise analogue accelerometers were attached to the ankle, wrist, hip, and torso to obtain features associated with acceleration and jerk. They found that the accelerometers located at the wrist and hip were better predictors of physical fatigue and that accelerometer features were stronger predictors of fatigue than heart rate features. To date, few studies have investigated the use of IMUs to obtain jerk and its use as an indicator of physical exertion and fatigue.

2.3 Jerk as a Measure of Motor Control

2.3.1 Detection of Physical Fatigue and Exertion

Jerk, the derivative of acceleration, is not widely studied in current non-clinical literature. In clinical literature, jerk is seen as a measure of motor control. Jerk is commonly used to (1) differentiate between pathological and non-pathological motions [62]–[64]; (2) quantify motion smoothness to assess motor learning and recovery [65]; (3) detect injury inducing motions [66]; and (4) measure performance fluency [67], [68]. Motor function abnormalities exhibited due to pathologies can be detected using jerk as a metric to quantitatively measure pathological tremor. On the same note, it is apparent that exercise-induced fatigue has a major impact on motor control and is responsible for a number of changes in neuromuscular function including increased physiologic tremor [51]. Physiologic tremor of a limb or other body parts occurs in non-pathological individuals, however, it becomes more pronounced when they experience fatigue or anxiety [69].

Experimental studies have found that expertise or task familiarity also impact motor control. Bril et al. [70] posits that skilled action combines smoothness, regularity, speed, precision, optimization, and adaptability. More practice produces smoother motion trajectories and thus minimizes jerk [63], [71]–[73]. As a result, jerk values observed for experts are expected to be lower than those observed for novices. Since fatigue degrades motor control, and thus motion smoothness, it is expected that jerk values will increase with fatigue. These increases however will be larger in magnitude than those due to physiologic tremors. In terms of risks of injury, being exposed to changes in motion can have significant biomechanical effects on the human body. During lifting tasks, jerk can be felt as the change in force on the body. Although the damping of the human body leads to some attenuation of rapid changes, the human body can experience biomechanical damages over time. It is important to note that motion smoothness is highly task dependent and must be considered when comparing jerk values between task types [64].

Two studies are notable and relevant to the current research. Maman et al. used IMU-collected motion data during simulated manufacturing tasks to determine acceleration- and jerk-based features that are predictive of fatigue occurrence [61]. Similarly, Zhang et al. used support vector machines (SVMs) to classify the occurrence of lower extremity muscle fatigue of gait [60]. These methods, however, have not assessed the feasibility of using machine learning techniques to recognize changes in jerk values during construction work.

2.3.2 Indicator of Skill Level

When the human body is introduced to a new movement, it learns the placement of different body parts, sequential muscle control, and coordination between muscles to achieve necessary positions. With time and repetition, the skill can be honed. According to Bril et al., a skilled action consists of smoothness, flexibility, precision, speed, adaptability, regularity, and optimization, and functionally coordinating these conditions is crucial [70]. Smoothness is achieved by purposefully repeating a movement and making necessary corrections to improve the motion [74]. The success of a human movement is judged by the smoothness of the motion, which can be quantified as jerk [75]. Thus, the smoother the motion, the lower the jerk.

There have been many attempts to describe the smoothness in a variety of movements. Previous studies have demonstrated differences in the smoothness of body movements with different levels of training, i.e., amateurs compared with professionals. These differences have been studied extensively in golf to better understand the mechanisms behind skilled golf performance. Choi et al. [76] evaluated the kinematic motion of amateur and professional golfers and found that professional golfers have smoother swings than amateur golfers. In this study, Choi et al. used jerk to quantitatively represent the smoothness of a motion to differentiate between skilled and unskilled golfers. A golf swing involves complex and continuous rotational movements of each joint in the body, and the muscle contraction sequence and timing of the impact between the club and ball are important components of a successful swing. Thus, a successful golf swing is achieved by rotating the harmoniously coordinating joint movements. Hreljac compared the jerk in the heel of skilled middle- to long-distance runners to that of other athletes (from soccer or tennis) during running and fast walking [74]. Hreljac concluded that the runners tended to exhibit significantly lower jerk, and thus smoother movements than non-runners during both running and fast walking. In addition, by analyzing jerk, Yan et al. found that the arm movement involved in overarm throwing becomes smoother as one becomes an adult [75]. More recently, Sakata et al. studied the effect of age-related changes in the smoothness of lower body joints during lifting, and demonstrated high jerk values in the ankle and hip joints of older subjects, pointing to less smooth movements in this group [77]. Nevertheless, studies investigating the smoothness of lifting movements are rare, and none have analyzed the smoothness during bricklaying. Like golf, bricklaying requires mastery that can be achieved through apprenticeships and on-site experience. However, unlike previously studied movements, bricklaying requires repetitive, high-intensity work.

2.4 Physical Fatigue in the Construction Industry

Despite technological advances, construction work continues to be a labor-intensive industry. Thus, the physical condition and health status of workers are vital to the successful completion of a project. However, MSDs are amongst the most frequently reported injuries and cause of lost time in the construction industry.

2.4.1 Investigating Masonry Work

An example of highly repetitive, highly physical, and non-structured environments is masonry work, which the subject of the following chapters. Energy use and oxygen consumption exceed recommended levels [78], [79], and trunk extensor fatigue has been observed in bricklayers performing highly repetitive work [80]. Block layers handle approximately 240–294 blocks per working day, resulting in a total weight of 3,200–3,600 kg per day [81]. Bricklayers are exposed to handling frequencies ranging from 87 to 262 bricks per hour [82].

The masonry workforce is composed of two classes: apprentices and journeymen. In Ontario, Canada the masonry apprenticeship program lasts for three years before a mason is examined to become a journeyman. A study shows that workers with less than five years of experience have higher rates of musculoskeletal injuries compared to journeymen with more than five years of experience [83].

2.5 Camera-based Systems

Mature technologies that capture body kinematics including the optoelectronic motion capture system as shown in Figure 1. The optoelectronic system is generally viewed as the 'gold' standard for kinematic measurement in a laboratory. Currently, the most common optoelectronic motion capture system is based on a combination of strobing lights and cameras that work in simultaneously to capture frames of position data taken from optical markers illuminated by the pulses of light. For each marker, several different camera angles are used to reconstruct and build a three-dimensional path representing segments and joints of the human body. On the other hand, optoelectronic systems are very expensive and offer best results in indoor capture conditions. This is because daylight interferes with the tracking of the marker. The size of their capture volume is relatively small, and it is relatively difficult and time-consuming to set up. Moreover, in practice, this method has limited use since it requires expertise, extensive post-processing, and large installation spaces [1]. Such limitations likely explain why relatively few studies have obtained detailed kinematics or kinetics in situ.

The first derivative of segment or marker position provides velocity and a second order derivative provides acceleration. This positional, velocity, and acceleration data is used to drive biomechanical models and study motion. However, while these systems are excellent at creating 3D images, they are lacking in the ability to accurately provide data of higher derivatives including accelerations.

Figure 1 Optotrak Certus active marker optoelectronic system

Markerless systems are based on two-dimensional data of one or more video cameras. They use computer vision algorithms and methods to track motion and depth of objects and humans. A once popular example are the Microsoft Kinect camera sensors. The main advantage of markerless motion capture systems is that the motion can be captured in a natural capture environment without the need to wear special equipment or marker for tracking. However, the main problem of markerless motion capture is that tracking requires close proximity with the object to be tracked to maintain a sufficient level of accuracy and information content. Objects in large distance to the camera cannot be captured in detail.

Since work environments can often influence specific work habits or strategies adopted and in turn affect the estimated level of physical exposure, the measurement of physical exposures should ideally be in situ. However, occupational physical exposures have been quantified in numerous studies in laboratory settings.

2.6 Inertial Sensor and Motivations for Use

Wearable sensors do not impose any restrictions on the motion with respect to lighting conditions and mobility. The sensors are light-weight and do not need any external cameras, emitters, or markers. The most common wearable sensors are inertial measurement units (IMUs) built from accelerometers, magnetic field sensors, and gyroscopes. Restrictions on the capture volume exists only with respect to the maximum allowable distance between the sender and receiver of the motion capture device and program. Its magnetometers, however, can be sensitive to magnetic and electrical disturbances in the environment. Among inertial sensors, accelerometers have been used extensively for activity recognition and studied with different body locations, number of sensors, classifiers, and feature sets [84]. Valero et al. developed an IMU system to detect unsafe postures of construction workers from motion data [4]. Ryu et al. used a single wrist-worn accelerometer-embedded activity tracker for automated action recognition [85], [86]. However, the use of accelerometers to monitor physical exertion or fatigue during physically demanding tasks has not been studied extensively.

Schall et al. assessed the IMU system in field-based occupational settings over an eight-hour work shift and suggested that the IMU system can achieve reasonably good accuracy and repeatability compared to the gold standard, optical motion capture systems [87]. Moreover, the light-weight and portability of wearable IMUs compared to external sensors, make them easy to attach to workers such as on construction vests, gloves, or helmet. IMUs, which combine accelerometers, gyroscopic and magnetic sensors, have been used by researchers to monitor ergonomically safe and unsafe postures during construction activities [14], [88]–[90].

The main commercial IMU motion capture system is Xsens [4]; other lesser known companies include Perception Neuron [91] which is significantly more affordable however, it is less robust in terms of hardware. Perception Neuron suits cost approximately $1,500 while the Xsens suits cost between $12,500 and $30,000. Perception Neuron IMUs, however, are extremely magnetically sensitive, so they must be used and stored away from tools, hardware, and electronics to prevent magnetic interference.

This research uses Perception Neuron wearable wireless inertial sensors and seeks to evaluate the use of acceleration and its derivative, jerk, to detect changes in motor control. In this application, there are several advantages to using inertial sensors.

The first major advantage is that a wearable system is extremely portable and can be applied wherever activity is occurring such as a construction site, in contrast to optical systems which require the activity to be performed in a laboratory environment. Before the advent of wearable motion sensors, optoelectronic systems were commonly used to track human motion [57]. However, the body segment positions they measure must be differentiated three times in order to obtain jerk. Since each numerical differentiation degrade the signal-to-noise ratio, repeating the process three times would magnify noise and thereby render the jerk values mostly meaningless [66]. In the case of IMUs, segment acceleration is collected directly and hence, jerk values can be obtained by differentiating only once. Thus, information that is lost in the optical system, can be detected by IMUs. The differentiation of acceleration to jerk also removes gravitational acceleration components. The greater precision of inertial sensors to measure higher derivatives such as acceleration, allows for the introduction of a new biomechanically-relevant metric, jerk.

Chapter 3 Identifying Physical Fatigue using the Jerk Metric

In this study, we tested the hypothesis that jerk can be used to detect changes in motor control arising from physical exertion. In addition, we investigated the differences in jerk values between motions performed by workers with varying skill levels. To our knowledge, no other studies have examined jerk as an indicator of fatigue for workers with varying levels of work experience.

Although it is known that fatigue contributes to an increase in physiological tremor and decline in motor control, there are no explicit studies that show the effect of fatigue on jerk. To test the hypothesis, we conducted a pilot experiment that involves a repetitive and targeted physically demanding exercise: the one-arm, bent-over dumbbell row. On the premise of the initial validation of the hypothesis, we proceeded to conduct a study on indoor masonry work involving participants with different levels of experience.

In the masonry trade, the everyday duties of bricklayers are physically intensive and highly repetitive. Working postures in bricklaying include frequent deep bending of the trunk while handling building materials, resulting in low back disc compression forces that exceed the NIOSH threshold value of 3.4kN [92]. Thus, bricklayers may suffer from physical fatigue, resulting in reduced motor control and strength capacity. This in turn leads to greater susceptibility to injuries and accidents. According to the Workplace Safety & Insurance Board of Ontario [93], the cost per claim for the masonry rate group ($50,882) was 144% greater than that of the average cost of a claim for all other rate groups belonging to the construction class ($20,818).

3.1 Pilot Experiment

A pilot experiment was designed to test whether physical fatigue results in increased jerk values and whether the signal-to-noise ratio of jerk derived from IMU-based motion capture suits was high enough to detect it. Three individuals, two males and one female, were recruited for the experiment. All were university students who reported moderate levels of daily physical activity and no previous injuries. The participants' mean (SD) age, stature, and body mass were 26.7 (3.1) years, 176.7 (5.8) cm, 78.3 (14.4) kg, respectively.

3.1.1 Methodology

All participants were fully rested before the experiment. Participants were asked to perform a one-arm dumbbell row exercise in a bent-over position with a 15 lbs dumbbell using their dominant arm. The dumbbell row requires the dominant upper limbs, specifically the biceps, shoulders, and side of back, to exert force and the non-dominant upper limbs to support and stabilize the body.

Each repetition consisted of an elbow flexion and extension, starting with the arm fully extended. The participants positioned themselves by kneeling over the bench and placing the supporting knee and hand on the bench as shown in Figure 2. The participants were asked to complete sets of twenty repetitions, with 30-second breaks between sets until they reached exhaustion or until they could no longer keep pace with a metronome set to 40 bpm. Jerk values during the first and last exercise sets were compared for each participant to detect differences between rested and fatigued states. The full-body kinematics of the participants were collected using a wearable IMU-based motion capture suit, Noitom Perception Neuron [91]. The sampling rate of the IMUs is 125 frames per second. The full-body suit is composed of seventeen IMUs located at the pelvis, sternum, head, and both shoulders, upper arms, lower arms, hands, upper legs, lower legs, and feet. Although not all IMUs were used, all seventeen IMUs were active during the experiment to enable system calibration. Each IMU sensor is composed of a three-axis accelerometer, a three-axis gyroscope, and a three-axis magnetometer. The hub collects the motion data from the Neuron sensors. Motion data was sent from the suit to a laptop via wireless connectivity. The sensors are secured to the body with Velcro straps as shown in Figure 3.

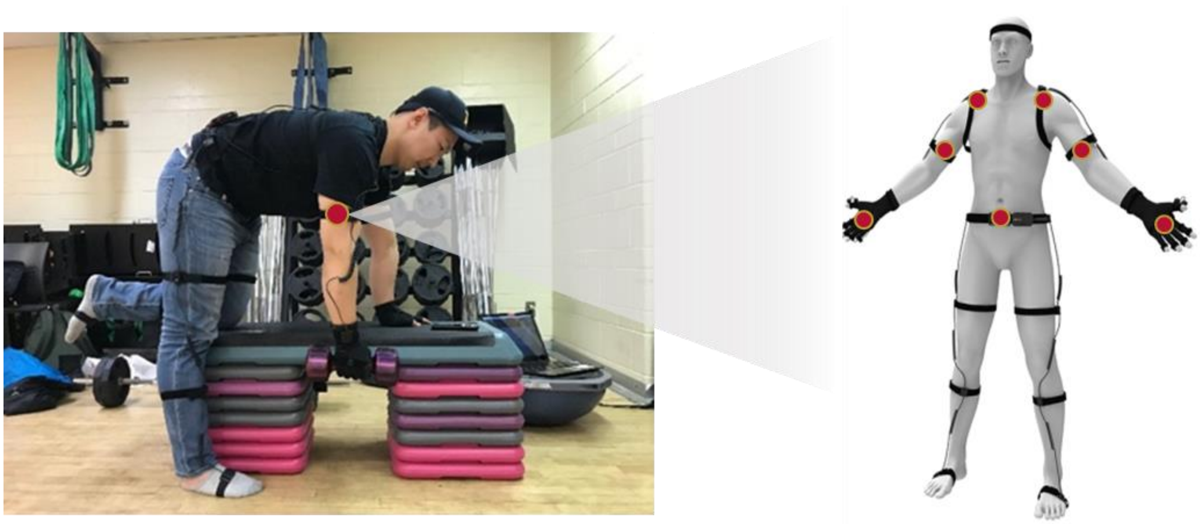

Figure 2 One-arm dumbbell

Figure 3 Neuron sensor, hub, and sensor straps

The exercise targets the upper limbs and torso area, seven body segments, namely the pelvis, and both the dominant and non-dominant upper arms, forearms, and hands, thus, these body segments were selected for jerk analysis. The sensor modules for the upper limb segments were strapped at the upper arms and forearms and placed at the backside of the hands using fingerless gloves. The gloves did not impair gripping ability of the participants. The sensor module for the pelvis segment was held in place at the lower back by a belt and waist buckle. Prior to the experiment, a calibration session, as demonstrated in Figure 4, was carried out to allow the Axis Neuron software to detect the placement and orientation of the sensors on the participant. The sensor-to-segment calibration was performed using three standard postures: A-pose, T-pose, and S-pose.

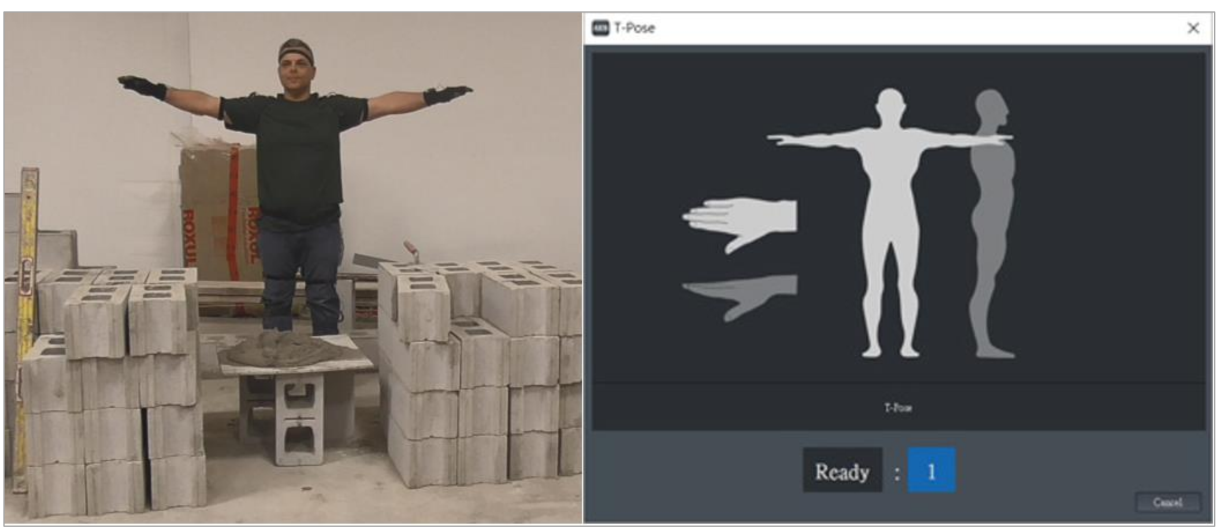

Figure 4 T-pose calibration process (pose 1 of 3)

3.1.2 Data Processing

The Axis Neuron software [91] visualizes and exports the calculation file data (.calc). This data type includes segment posture quaternion in segment coordinate; displacement, speed in ground coordinates; original acceleration and gyro data in module coordinates. The Cartesian components of the segment acceleration are collected from the IMU's accelerometer.

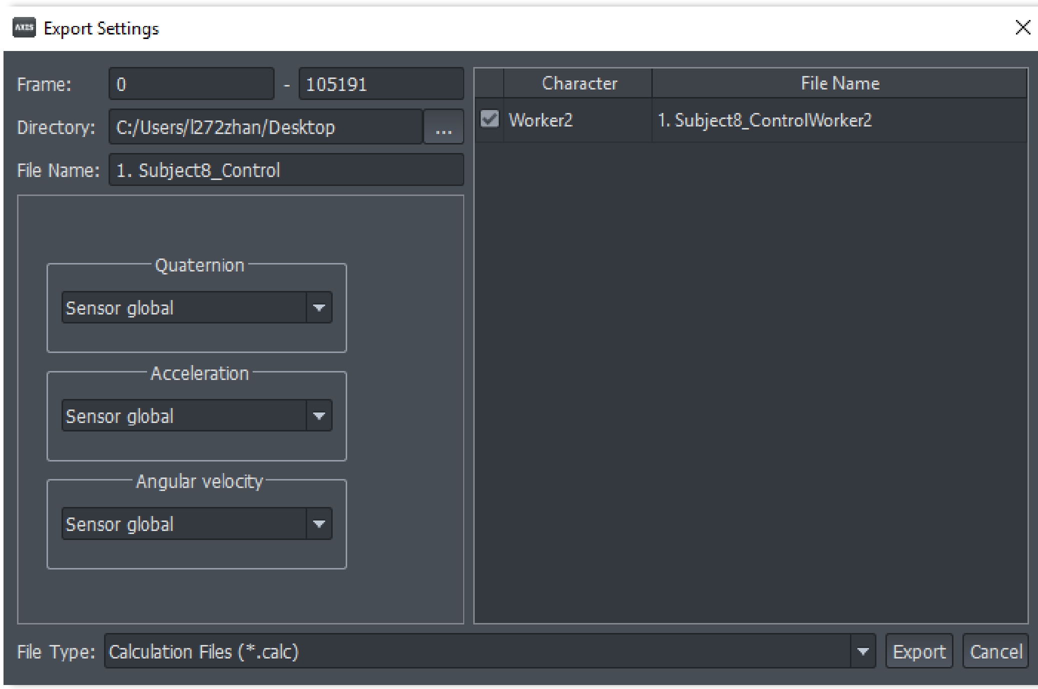

Figure 5 Exporting calculation file from raw file

For each of the seven IMU sensors, the resultant acceleration data were calculated from its Cartesian components. A low-pass Butterworth filter with a 10 Hz cut-off frequency was then used to remove high frequency noise. Jerk was calculated as the time-derivative of the acceleration magnitude (da/dt). Average jerk values were calculated for the first set of the exercise to represent each participant's rested characteristic jerk, J_r, and for the last set to represent their fatigued characteristic jerk, J_f. A visualization of the data is shown in Figure 6.

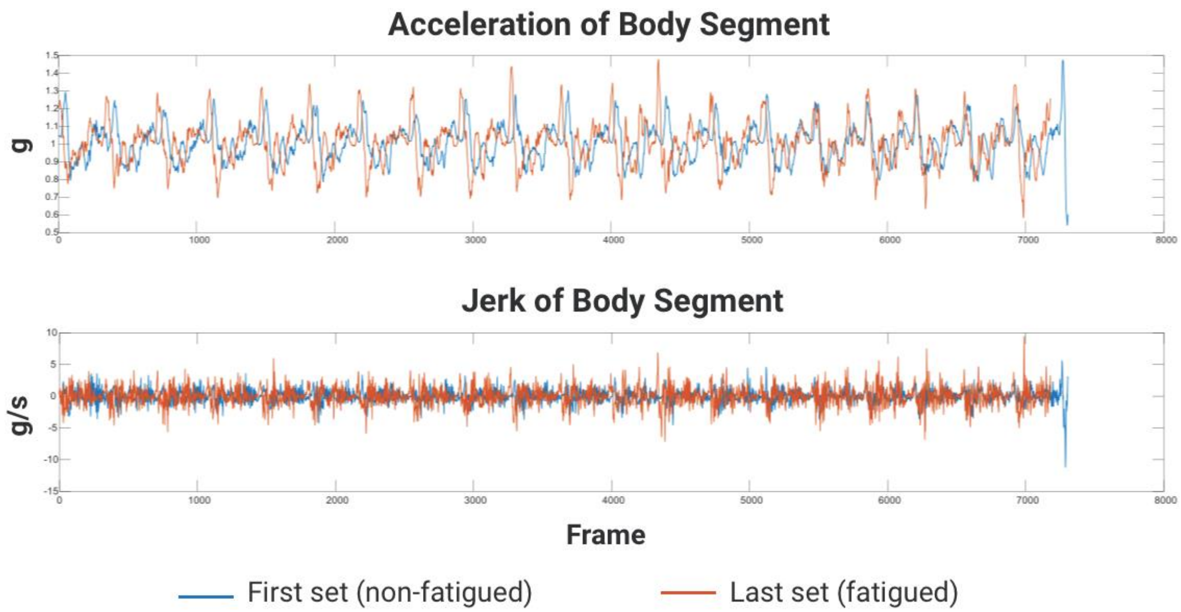

Figure 6 Resultant acceleration to jerk data - first and last set

3.1.3 Results

On average, the three participants completed seven sets of twenty repetitions. The results show that the characteristic jerk for all participants and all seven segments increased significantly from the rested to the fatigued states as shown in Figure 7. As expected, the jerk magnitudes of the participants' dominant upper limbs were much greater than the pelvis and non-dominant upper limbs. The greatest percent increase between the rested and fatigued characteristic jerk values was observed at the pelvis. For both the dominant and non-dominant upper limbs, the upper arm had a greater percent increase compared to the hands and forearms. Additionally, a greater percent increase was observed between the characteristic jerk values of the non-dominant upper limbs compared to those of the dominant upper limbs. This may indicate that although the non-dominant upper limb does not take part in the main lifting motion, its role as the stabilizer can also become compromised as the participant becomes fatigued. It is interesting to note the wide interpersonal variability in both jerk magnitude and change in jerk values between their rested and fatigued states.

The pilot experiment confirmed the hypothesis that the sensors used were sensitive enough to detect a change in jerk values over the duration of a repetitive and targeted physically demanding exercise. The following experiment on a bricklaying task, tests the same hypothesis, however, in a realistic environment that respects between-subject variabilities including technique and pace.

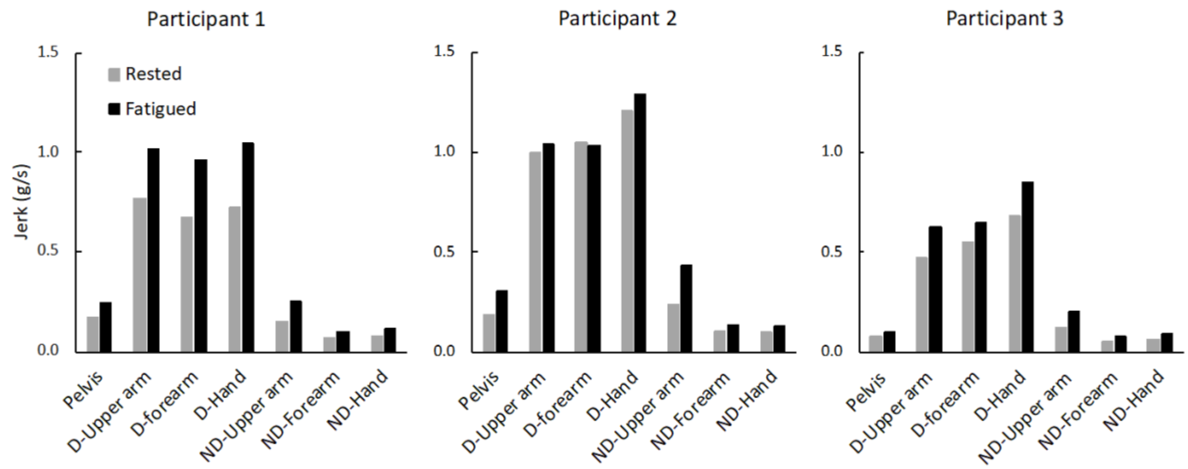

Figure 7 Jerk values of pelvis and dominant (D) and non-dominant (ND) upper limbs during a one-arm dumbbell row exercise

3.2 Bricklaying Experiment

In the bricklaying experiment, jerk analysis was carried out on eleven body segments, namely the pelvis, the dominant and non-dominant upper limb segments (upper arms, forearms, and hands) and the dominant and non-dominant lower limb segments (thigh and shank), since lifts involve whole-body work [94]. Those body segments were hypothesized to be the most suitable for fatigue detection since bricklaying requires large ranges of motion, forceful contractions, and high precision from the upper and lower limbs. The torso was selected due to frequent bending which may result in lower back muscle fatigue. Locations of the investigated sensor modules are shown in Figure 8. Previous activity monitoring studies for similar tasks were used as a guide for sensor location selection [61], [83]. The objectives of this experiment were: (i) to assess the suitability of jerk as a metric of physical exertion during a bricklaying task, and (ii) to examine the relationship between jerk and level of expertise.

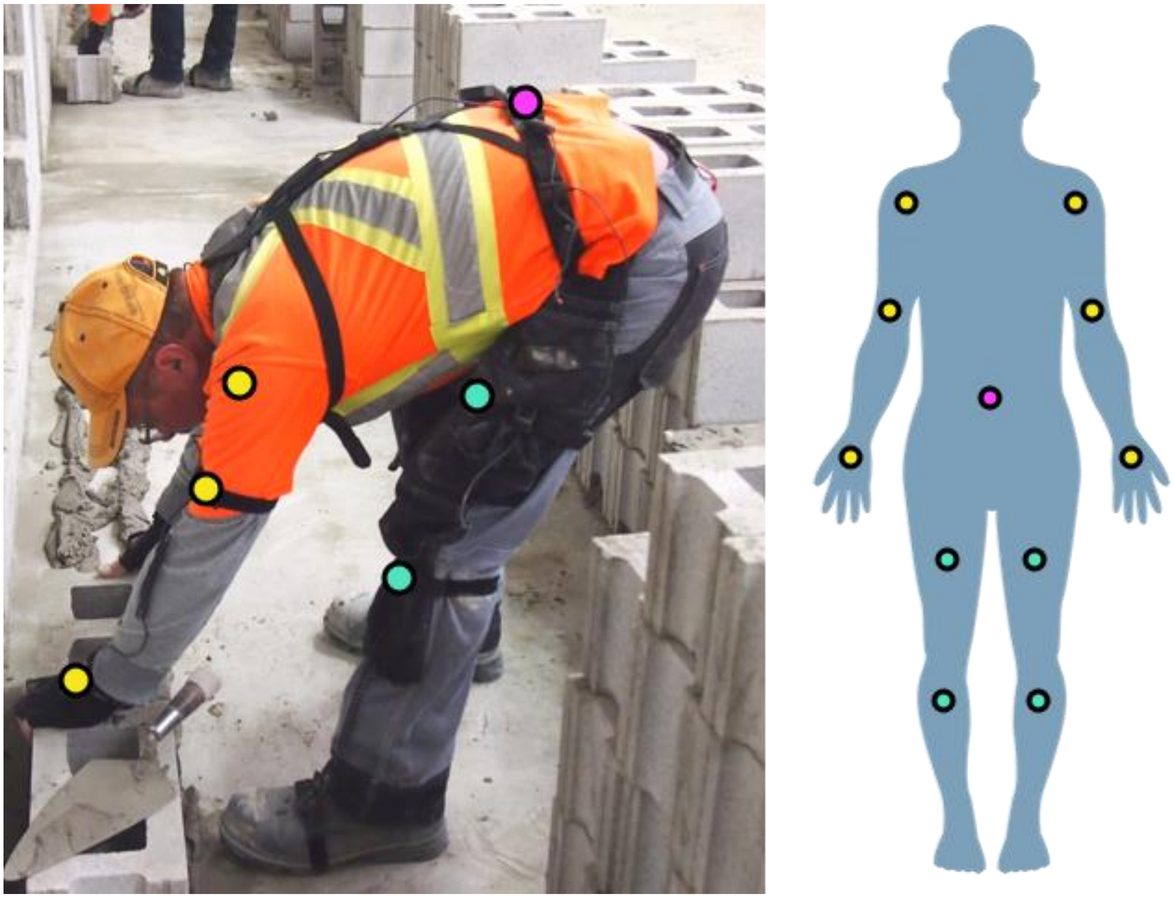

Figure 8 Investigated IMU sensor locations

3.2.1 Methodology

3.2.1.1 Office of Research Ethics

Approval from the University of Waterloo's Office of Research Ethics was obtained to conduct experiments with human participants at the Canadian Masonry Design Center (CMDC). This process required a Consent to Participate form and a Consent to Use Video and/or Photographs form to be signed by each participant and a formal means of appreciation to the participants for their time and effort.

3.2.1.2 Participants

The experiment was conducted at the CMDC, indoor training facility in Mississauga, Ontario. Thirty-two male bricklayers with varying levels of masonry experience were recruited. In Ontario, Canada the masonry apprenticeship program is three years long, after which, an apprentice is examined to become a journeyman. Participants were grouped into four experience groups including (1) novices, (2) first-year apprentices, (3) third-year apprentices, and (4) journeymen with an average of 22 years of masonry experience. Novices and apprentices are classified as inexperts. Participant demographics are shown in Table 1. The study was approved by the Office of Research Ethics at the University of Waterloo.

Table 1 Participant demographics

Experience Group	Experience (years)	No. Participants	Height (SD)	Weight (SD)
Novices	0	12	185.06 (5.82)	87.92 (15.64)
First-year Apprentices	1	5	182.36 (3.64)	98.96 (18.69)
Third-year Apprentices	3	6	184.20 (4.02)	93.80 (24.89)
Journeymen	22	9	178.89 (4.99)	89.11 (12.59)
Total	--	32	182.52 (5.48)	90.21 (16.99)

3.2.1.3 Instrumentation

Whole-body kinematics of the participants were collected with the same wireless IMU-based motion capture suits used in the pilot experiment. Before the start of the experiment, the same suit calibration procedure mentioned in the pilot experiment was completed. The participants followed standard worksite procedure and mortar and block supply were provided by a helper as needed. The experiment was captured on video using two video cameras. Continuous motion and video data were collected until the lead wall was completed. During the data processing phase, the visualization of the participants' motions provided by the Axis Neuron Software were used for task synchronization to identify the start and end time of each lift and to segment the lifts from other subtasks, such as spreading mortar. Video recordings were used as a visual aid for task segmentation by manually synchronizing the recording to the skeletal figure of the participants generated on Axis Neuron.

3.2.1.4 Experimental Procedure

Each participant was instructed to complete a pre-built lead wall, Figure 9(a), using forty-five concrete masonry units (CMUs) from the second to the sixth course where a course is defined as a layer of CMUs. Thus, the bricklaying task consisted of forty-five individual 'lifts', consisting of picking up, moving, and laying down of a block. The CMUs were Type "A" concrete units, each weighing 16.6 kg with dimensions of 390 x 190 x 100 mm. The blocks were placed in three piles approximately one-meter away from the pre-built lead wall. Two panels of mortar were placed between the three block piles, shown in Figure 9(b). The use of mortar and the requirement of participants to meet alignment tolerances, established a level of realism by approximating true field work. Figure 10 shows a participant completing the bricklaying task.

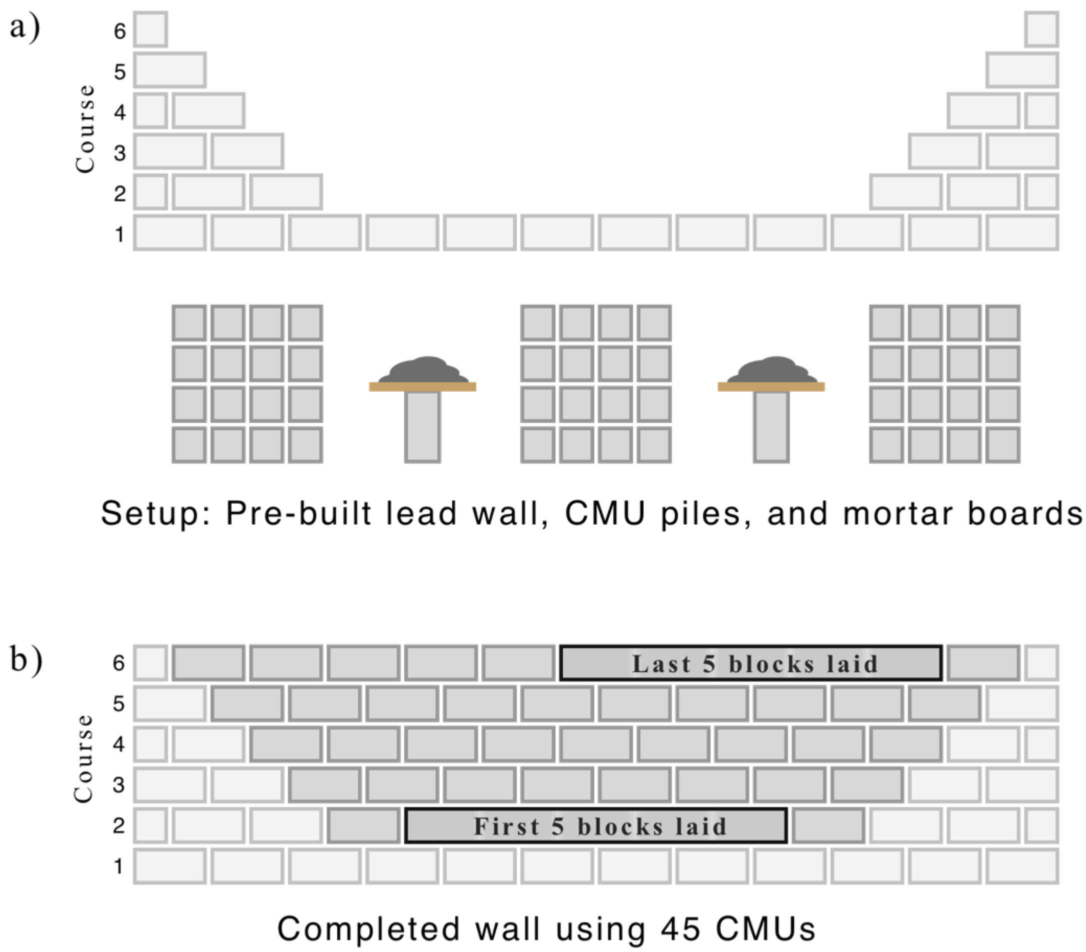

Figure 9 Setup of the bricklaying experiment

Figure 10 A participant completing a pre-built lead wall

3.2.2 Data Processing

Following the experiment, the motion data collected with the IMU suit was exported as spreadsheet files containing the linear acceleration of all seventeen body segments over the duration of the bricklaying task. Figure 11 shows the schematic diagram for the data processing from raw motion data. Only eleven of the seventeen body segments available in the motion data were used including the pelvis, dominant and non-dominant upper arm, forearm, hand, thigh, and shank. Although not all IMUs were used, all seventeen IMUs were active during the experiment due to the suit configuration. Following the data processing procedure described in the pilot experiment, the motion data were segmented into individual lifts and converted to MATLAB readable .mat files. All further data analysis was conducted in MATLAB.

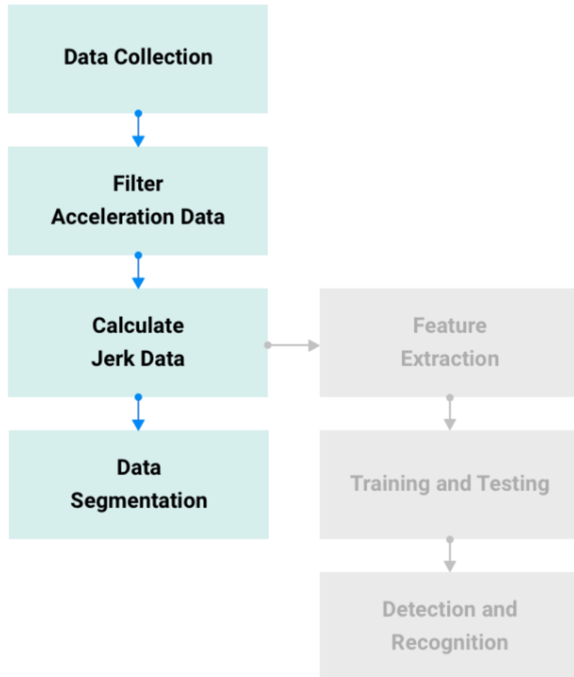

Figure 11 A schematic diagram of data processing from raw motion data

As performed in the pilot experiment, the resultant acceleration of the eleven body segments in question were calculated from their Cartesian components and filtered using a low-pass Butterworth filter with a 10 Hz cut-off frequency to attenuate high frequency noise. The average jerk values were found for the first five lifts of the bricklaying task to represent each participant's rested characteristic jerk, J_r, and for the last five lifts to represent their exerted characteristic jerk, J_e. The first and last five blocks defining each state are illustrated in Figure 4(b). The average of both characteristic jerk values, $(J_r)_{avg}$ and $(J_e)_{avg}$, were found for the four experience groups. An unpaired (two-sided) t-test was carried out to determine the significance of differences between the characteristic jerk values of the rested and exerted states for each group.

3.2.3 Productivity Loss

Productivity loss is frequently perceived or used as a metric to identify fatigue [95]–[98]. Thus, productivity loss was used as another indicator of physical exertion. Each participant's overall productivity was measured as the number of laid blocks per minute. At the end of the task, the completed wall was visually assessed to ensure acceptable build quality. To determine if the participants' working pace was decreasing over the duration of the task, the average time taken to lay one block for each course, t_i, was found for each experience group from the second course to the sixth course. The averages were then normalized with respect to the second course average, t_2.

3.2.4 Results

For each experience group, the mean and standard deviation of the jerk values in rested and exerted states are listed in Table 2. We found that jerk was lowest for journeymen and highest for third-year apprentices across all eleven body segments under study. The first-year apprentices had the second highest jerk values followed by the novice group for all three segments of the dominant upper limb; the opposite was true for the non-dominant upper limb. On the other hand, the novice group had the second highest pelvis and lower-limb jerk values followed by first-year apprentices. Participants whose jerk values did not increase from the rested to exerted states are summarized in Table 3. These participants, however, were all included in the jerk analysis. The jerk value for one or more segments did not increase for 8 out of the 32 participants. None of those participants were journeymen. The pelvis jerk was the most sensitive parameter with only 3 inexpert participants failing to show an increase in the characteristic jerk value from rested to exerted states.

The pelvis jerk values and standard deviations were smallest compared to the upper limb segments. These values increased along the upper arm kinematic chain reaching maxima at the hands. On average, jerk values and standard deviations of the dominant upper limbs were greater than those of the non-dominant upper limbs for all four experience groups. The same is true for the lower-limbs, however the differences between the jerk values of the dominant and non-dominant lower limbs were much smaller.

Table 2 lists the statistical significance of the difference between rested and exerted jerk values obtained from the t-test for each group and each segment. Where the *p*-values were found to be larger than $p>0.05$, we determined that no significant differences (NS) exist between the rested and exerted jerk values. The results show significant increases between the characteristic jerk values for all eleven body segments of journeymen. For all other experience groups, no significant differences were seen between the characteristic jerk values for the body segments except for the pelvis, thigh, and shank jerk of novices and pelvis and thigh of first-year apprentices.

Table 2 Means, standard deviations, and statistical significance for jerk (g/s) of eleven body segments

	Dominant Limbs					Non-dominant Limbs				
	Rested		Exerted		p	Rested		Exerted		p
	$\bar{x}$	*SD*	$\bar{x}$	*SD*		$\bar{x}$	*SD*	$\bar{x}$	*SD*	
Novices										
Pelvis	2.40	0.76	2.82	0.87	0.004*	-	-	-	-	-
Upper arm	4.08	1.71	4.29	1.37	NS	3.72	1.27	4.04	0.95	NS
Forearm	5.34	2.93	5.82	2.45	NS	4.18	2.32	4.83	1.62	NS
Hand	5.99	3.76	6.50	3.12	NS	4.60	2.55	5.07	1.70	NS
Thigh	4.42	0.01	5.35	0.03	0.008*	4.58	0.01	5.29	0.43	0.032*
Shank	4.91	1.88	5.64	2.00	0.034*	4.83	1.65	5.58	2.15	0.030*
First-year										
Pelvis	2.08	0.50	2.34	0.40	0.045*	-	-	-	-	-
Upper arm	4.24	1.62	4.16	0.95	NS	3.31	0.72	3.63	0.75	NS
Forearm	6.26	3.03	5.94	2.20	NS	3.79	0.95	3.99	1.33	NS
Hand	7.03	3.29	6.71	2.78	NS	4.14	1.06	4.28	1.95	NS
Thigh	3.64	0.01	4.56	0.05	0.003*	3.98	0.04	4.44	0.81	0.046*
Shank	3.87	1.29	4.61	1.52	NS	4.22	0.97	4.32	1.31	NS
Third-year										
Pelvis	2.67	0.58	2.69	0.62	NS	-	-	-	-	-
Upper arm	5.04	1.85	4.69	0.99	NS	4.62	1.10	4.49	1.09	NS
Forearm	6.71	2.92	6.17	1.75	NS	5.22	1.55	5.22	1.78	NS
Hand	7.90	3.94	7.08	2.72	NS	5.46	1.69	5.55	1.90	NS
Thigh	5.10	0.55	4.85	0.83	NS	5.05	0.92	4.97	0.32	NS
Shank	5.60	1.85	5.14	1.45	NS	5.18	1.25	5.19	1.67	NS
Journeymen										
Pelvis	1.57	0.47	2.20	0.52	<0.001*	-	-	-	-	-
Upper arm	2.96	0.83	4.21	1.37	<0.001*	2.86	0.69	3.92	1.03	<0.001*
Forearm	3.79	1.53	5.30	1.78	<0.001*	3.04	0.93	4.80	1.76	<0.001*
Hand	4.40	2.27	6.04	2.36	<0.001*	3.41	1.30	5.40	2.39	<0.001*
Thigh	3.27	0.01	4.15	0.01	<0.001*	2.72	0.01	4.07	0.01	<0.001*
Shank	3.16	1.42	4.08	1.27	<0.001*	2.76	1.07	3.86	1.24	<0.001*

Table 3 Number of participants whose segment jerk values did not increase from rested to exerted state

Group	Pelvis	Upper Arm	Forearm	Hand	Thigh	Shank	Total
Novices	1	2	2	3	2	3	3
First-year	–	2	2	2	–	–	2
Third-year	2	2	2	3	3	3	3
Journeymen	–	–	–	–	–	–	–

As expected, journeymen were found to be the most productive with the highest blocks/min count, followed by third-year apprentices, first-year apprentices, and novices. The total time to complete the task for each experience group is summarized in Table 4. The association between experience and productivity is apparent. The average time taken to lay one block for each course t_i, normalized with respect to the average time taken to lay a block at the second course t_2, is shown in Figure 6 for each experience group. The normalized time taken to lay a block for each course indicate changes in pace over the duration of the task. The figure shows that time per block increased and pace dropped significantly for novices and moderately for first-year and third-year apprentices but remained almost constant for journeymen.

Table 4 Task completion time and productivity of four experience groups

Group	Total Task Completion Time (min)		Mean Rate
	$\bar{x}$	*SD*	(Blocks/min)
Novices	59	23	0.76
First-year	43	10	1.05
Third-year	41	3	1.10
Journeymen	28	5	1.61

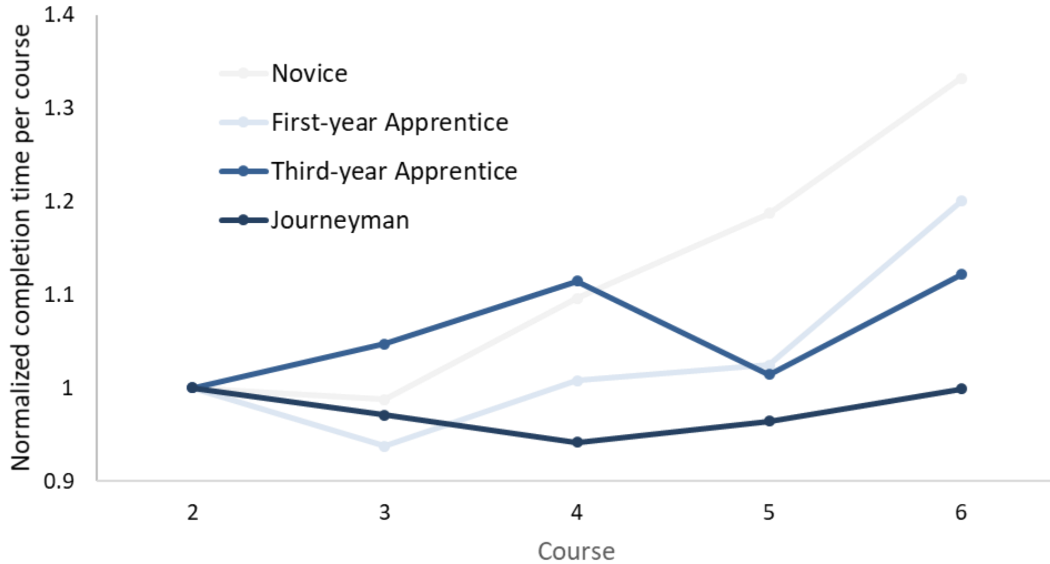

Figure 12 Normalized completion time per course for four experience groups

3.2.5 Discussion

In this study, we investigated the use of jerk as a metric to measure motor control changes arising from physical exertion. We also investigated the differences among jerk values for motions of workers with varying levels of expertise and among jerk values for different body segments of the same worker. The results of the pilot study suggest that the signal-to-noise ratio of jerk derived from IMU-based motion capture suits was high enough to detect differences between rested and exerted states. These results were confirmed by the findings in a bricklaying experiment which showed that jerk values for all journeymen's eleven body segments under study had sufficient signal-to-noise ratio to distinguish between rested and exerted states with a confidence level better than 99%. This finding, however, was not true for inexpert participants.

The standard deviations of the rested and exerted characteristic jerk values increased along the kinematic chains going from the pelvis to the hand and from the pelvis to the shank. We hypothesize that spurious acceleration signals caused by contact and impact events between the hands and the CMUs and the feet and ground raised the noise floor of the acceleration signal, which were further amplified by the numerical differentiation to obtain jerk. Spurious acceleration signals diminish as they travel down along the kinematic chain extending from the hands to the pelvis [99]. As a result, the standard deviation of jerk decreased, and the signal-to-noise ratio improved for segments closer to the body center of mass. This may explain our finding that the rested and exerted characteristic jerk values can be distinguished for pelvis segments of novices and first-year apprentices with a greater than 95% confidence level but not for any of their upper limb segments.

Each experience group in the bricklaying experiment demonstrated a characteristic behavior. Journeymen performed lifts with the lowest jerk values of all experience groups, demonstrating smooth motions and a high degree of motor control. They were also able to maintain a high productivity rate of 1.61 blocks/min throughout the task. Our findings are consistent with other studies involving the relationship between jerk and expertise. Gaudez et al. [100] found that the more experience a person has in performing a task, the better and more efficient they are at selecting relevant information from the surroundings and formulating preparatory movements. Additionally, Balasubramanian et al. [64] found that the less experience a person has in performing a task, the more intermittent their movements are. Thus, it appears that with experience, learned motions are successfully transformed to expert techniques that reflect safe and efficient lifting motions. In contrast, third-year apprentices performed lifts with the greatest jerk values, indicating inferior motor control. This finding is consistent with Alwasel et al. [83] who found that third-year apprentices undergo the highest joint forces and moments while journeymen undergo the least forces and moments. It is also in line with the U.S. Bureau of Labor Statistics [101] report that show injury rates were greatest for workers with less than five years of experience with the same employer. The productivity of third-year apprentices (1.10 blocks/min) was also less than that of journeymen.

Using an EMG-assisted biomechanical model, Marras et al. examined how spine loading changes as a function of experience, lift frequency, and lift duration while repetitively lifting over the course of an 8-h workday. It appears that the greatest spine loads occurred at those lift frequencies and weights to which the workers were unaccustomed. These observations might help explain the high injury and turnover rate often observed in new workers [102].

During the experiment, the competitive nature of the trade was evident and expressed through verbal communication between third-year apprentices and journeymen. Anecdotal evidence gleaned over casual interviews during the experiment revealed that the competitive nature of bricklayers also exists on the job. The pressures to match production levels may have led third-year apprentices to use jerkier motions and greater effort than they may be physically prepared for. Thus, individual physical characteristics or ability to endure physical exertion could be the cause of different patterns of correlation between exertion and productivity in the four experience groups. In contrast to third-year apprentices, journeymen may not only have greater expertise but may also be physically better adapted to achieve higher production levels.

The standard deviations of the task completion time for each experience group were much smaller for third-year apprentices and journeymen compared to novices and first-year apprentices. This decrease in the variation between completion times of more experienced individuals may have resulted from their adoption of a consistent work regimen along with the pressures to complete the task at a similar work pace to their peers. Novices and first-year apprentices appear to have greater motor control than third-year apprentices, however they have the lowest productivity at 0.76 blocks/min and 1.05 blocks/min, respectively. It appears that their inexperience and greater caution toward injury make them more careful when performing their task. This conclusion is supported by a previous clinical study. Slaboda et al. [63] found that subjects with chronic lower back pain (CLBP) performed lifts with significantly lower jerk values than healthy subjects. Following rehabilitation, subjects with CLBP were shown to have similar jerk values to that of control subjects. This suggests that subjects with CLBP regulated their motions to achieve smoother motion patterns and avoid infliction of pain, whereas control and rehabilitated subjects may have had an alternate motive to lift with greater efficiency. Since participants were not instructed to complete the task within a fixed time frame, novices and first-year apprentices may have been more inclined to adjust their work pace according to their comfort level. Adjustment in work pace may have been an underlying reason for the participants whose jerk values did not increase over time. It is interesting to observe that across a variety of motor tasks an individual's preferred rate of work has been shown to be the most economical, such that at a rate slower or faster than preferred or “freely-chosen" metabolic energy expenditure relative to work output is higher than at the preferred rate [103]. Corlett and Mahadeva demonstrated the relationship between work rate and economy using simulated work tasks, showing that freely chosen work rate was lowest in physiological cost and, therefore, more economical relative to work rates faster or slower than preferred [104].

For the journeymen, a detectable difference was found between their rested and exerted characteristic jerk values, indicating physical exertion. Their work pace however, remained relatively constant throughout the task. This is consistent with a previous study by Lee and Migliaccio [98] which demonstrated that for high-productivity workers, productivity increased as physical strain, indicated by heart rate, increased. They also found that the effect of strain on productivity was much less significant for high-productivity workers compared to low-productivity workers. Our results show that jerk may be a better, more sensitive, method for fatigue assessment in experienced workers where fatigue and productivity are not necessarily correlated. Furthermore, similarities can be drawn between the high levels of physical conditioning and productivity developed through experience to those developed through work hardening, an individualized treatment program that assists injured workers to regain productivity levels to match industry expectations [105].

Although results show significant increases between the characteristic jerk values for all eleven body segments of journeymen, no significant differences were found between the characteristic jerk values of all other experience groups except for the pelvis and lower-limbs of novice and first-year apprentices. Our findings also reveal that participants who did not show an increase in jerk values between rested and exerted states belonged to the novice and apprentice groups. This may be due to those participants changing their pace and, thereby, reducing their exertion level.

While the effects of demographic variables, such as age and sex, were not considered, the recruitment process was not selective, and the participants reflect the demographics of construction industry in Ontario. Therefore, the conclusions drawn from each experience group should be an accurate reflection of the construction population. In the literature, lifting injuries have been shown to increase significantly after the age of 50 [106]. However, highly trained workers may be able to outperform those that are much younger since moderate to high intensity work has been shown to improve or maintain physical health and functional capacity [107]. Anecdotal evidence in this study seems to support this finding; journeymen, although consistently and significantly older than apprentices, were better physically conditioned for the work task.

3.3 Study Limitations

A few limitations pertaining to the present work are noteworthy. First, the design of the bricklaying experiment allowed some inexpert workers to self-pace, thereby, reducing their exertion levels. This allowed us to examine the relationships among experience level, fatigue, and productivity but it may also have resulted in lower levels of physical exertion and insignificant changes in jerk values for inexpert masons. Follow-up studies should be designed to control against self-pacing and to extend over longer periods. Currently, biomechanical and fatigue-related investigations have been restricted to analyses of brief periods of lifting and are assumed to represent those completed throughout an entire workday. However, several studies exploring motor recruitment patterns resulting from fatigue suggest that repetitive lifting over the course of an extended period may indeed influence the motor recruitment pattern and result in changes in the loading pattern on the body. Exploring the effect of fatigue during long duration lifting bouts is expected to be more indicative of fatigue development and associated risks of injuries over a workday [108], [109] .

Second, this study examines the relationship between physical exertion and jerk at the group level. Based on Table 2, statistically significant differences between the rested and exerted jerk values were confirmed only for the journeymen and attributed to their adoption of similar work techniques and work pace. As seen in the pilot experiment, the interpersonal variabilities of jerk magnitudes at rested and exerted states were high. Thus, future studies may examine the relationship of physical fatigue to jerk on an individual level by using learning algorithms to determine intrapersonal variabilities in jerk. The results may uncover intrapersonal increases between rested to exerted jerk values for all other experience groups where significant increases were not seen on a group level.

Third, in its current form, the data processing method requires manual segmentation to distinguish 'lifts' from other subtasks, such as spreading mortar, since jerk is highly task dependent. Future work should investigate algorithmic methods to either allow for the continuous collection of acceleration data without the need for manual task segmentation or the automation of task segmentation.

Lastly, further research is required to establish jerk thresholds corresponding to fatigue and physical exertion levels that may impact workers' health, safety, productivity or work quality so that it can be used to develop warning systems against high levels of physical fatigue or as an indicator of recovery following fatigue. Such understanding would foster the design of enhanced work schedules and other methods to protect worker health and safety and maintain productivity and quality.

3.4 Conclusion

The objectives of this study were to assess the suitability of jerk as an indicator of physical exertion and fatigue over the course of a demanding task and to examine the relationship between jerk and experience level. As a proof of concept, the method was first tested on participants completing the one-arm dumbbell row until physical exhaustion was reached. The results of the pilot study suggested that jerk values of body segments can detect fatigue and that accelerations obtained from motion capture suits have enough signal-to-noise ratio to detect differences between rested and exerted states. Following the pilot experiment, the method was then demonstrated on a study of masonry work.

In the bricklaying experiment, jerk was lowest for journeymen and highest for third-year apprentices across all eleven body segments under study. These results suggest that the experience journeymen gain over the course of their career improves their ability to perform repetitive heavy lifts with smoother motions and greater control. Third-year apprentices performed lifts with the greatest jerk values, indicating poor motor performance. This finding is consistent with previous literature that found that third-year apprentices use forceful, less ergonomic, lifting techniques in order to match journeymen's production levels. Novices and first-year apprentices showed more caution towards risks of injury, moving with better motor control, compared to more experienced third-year apprentices. Their production levels, however, falter behind the production levels of other experience groups. We speculate that inexperience and less social pressure on novices and first-year apprentices allowed them to maintain motor control through work pace modification resulting in lower fatigue levels and jerk values compared to third-year apprentices. Detectable increases between the characteristic jerk values were found only for the journeymen experience group, which is attributed to greater interpersonal similarities in learned technique and work pace.

It is important to note the sensitivity of the IMU-based system to the level of the noise floor in the underlying acceleration signal. As such, care should be taken to attach sensors to body segments involved in the task while being as far as possible from shocks and impacts.

The results of this study provide insight into the stage of training at which intervention may be required to manage motions performed with poor motor control. These interventions may include modifications to the training regimen and work-rest cycles to prevent consistently higher levels of physical fatigue. Furthermore, the proposed method can be further simplified, and its costs can be further reduced by minimizing the number of IMUs used to only one or a few sensors. This will enable practical and effective on-site detection of physical fatigue.

Chapter 4 Automated Monitoring of Physical Fatigue using Machine Learning

Construction work is typically physically demanding and can result in a high number of accidents and injuries caused by fatigue. Fatigue can also have a detrimental impact on workers' judgement, productivity, and quality of work. Although accident and injury prevention has become a primary area for improvement within the construction industry, fatigue prevention and detection continue to involve manual observation or self-reported subjective assessments. The inherent subjectivity of these methods has prompted the introduction of biomechanical and physiological assessments that quantify fatigue levels, thereby increasing reliability while reducing the time and human resources needed for their implementation. Despite extensive research that confirms the validity of these assessments, they can be cumbersome and or intrusive because they often require that multiple sensors and wires be attached to the worker, or need external devices that work in conjunction to worn devices. These assessments also often require tasks that involve several sequential activities or motions to be manually segmented; this is not only a time-consuming process, but it eliminates the applications of these assessments for real-time feedback and consumer use.

The availability of wearable systems capable of automatically classifying human physical motion is extremely attractive for many applications in the field of healthcare monitoring and in developing advanced human-machine interfaces [84]. IMUs offer several advantages over the traditional assessments, for example, they are cost-effective, non-intrusive, and wireless.

This research investigates the use of support-vector machines (SVM) to automate the monitoring of physical exertion levels using jerk. The detection of high levels of exertion would allow workers to take proactive measures in mitigating adverse effects of fatigue.

4.1 Machine Learning Applications for Activity Recognition

Multiple studies have examined the influence of fatigue on the kinematics and kinetics of movement execution. Moreover, artifical neural networks (ANNs) have been widely used, particularly in sports and clinical biomechanics, to classify human movement. Supervised classification techniques include k-Nearest Neighbour (k-NN), Support Vector Machines (SVM), Gaussian Mixture Models (GMM), and Random Forest (RF), and unsupervised classification techniques include k-means, Gaussian mixture models (GMM) and Hidden Markov Model (HMM).

The focus of this work is to classify with SVM. Many studies with SVM have been reported in the field of activity recognition, although they do not focus on the study of fatigue.

As outlined by Maman et al., for effective technological approaches to physical fatigue measurement, it is essential that the system can: 1) predict physical fatigue prior to a detrimental productivity/safety impact, 2) monitor physical fatigue in the operational environment to allow for intervention when deficits are identified, and 3) account for individual variabilities in the underlying physiological functions required to establish individualized baseline conditions as opposed to a population condition [61].

In our previous work [110], we found that jerk may be used as an indicator of loss of motor control caused by physical exertion. However, the tasks were manually separated to ensure that jerk values were compared between the same action types, for examples, the motion data collected during each lifting action (pick up – transport – lay down) were segmented out from other motions such as spreading mortar. Manual segmentation of the data prevents this method from being used for real-time assessments. In this study, we conducted two sets of analyses: 1) we tested the feasibility of analyzing jerk values using continuous motion data collected from our previous study to monitor changes in motor control, and 2) we conducted a second experiment that evaluates changes in jerk values between two identical bricklaying tasks following a series of exhausting exercises. Continuously monitoring jerk is investigated in the present study using IMU sensors and SVMs, which have been used extensively to classify human motion patterns and activities [89], [111]. Given that rested and exerted states can create unique jerk signal patterns, machine learning algorithms using motion data may be used to monitor the development of physical exertion in real-time for practical applications. . In this work, we also examine the inter- and intra-subject differences of experienced workers to account for individual variabilities in the underlying physiological functions that affect motor control.

4.2 Methodology

4.2.1 Participants

The experiment was conducted at the Canadian Masonry Design Center (CMDC) indoor training facility in Mississauga, Ontario. Six male bricklayers with an average of 22 years of masonry experience were recruited for the experiment. The participants' mean (SD) stature and body mass were 179.0 (5.0) cm, 89.3 (14.1) kg, respectively. The study was approved by the Office of Research Ethics at the University of Waterloo.

In our previous work, experienced masons displayed statistically significant inter-subject differences between the rested and exerted jerk values over the duration of a bricklaying task. The statistically significant differences between experienced masons was attributed to greater inter-subject similarities compared to unexperienced masons in their learned technique and work pace. In this work, we examine both the inter- and intra-subject differences of experienced workers.

4.2.2 Instrumentation

The segment kinematics of the participants were collected using a wearable IMU-based motion capture suit, Noitom Perception Neuron [91]. The sampling rate of the IMUs is 125 frames per second. The full-body suit is composed of seventeen IMUs located at the pelvis, sternum, head, and both shoulders, upper arms, lower arms, hands, upper legs, lower legs, and feet. Although not all IMUs were used, all seventeen IMUs were active during the experiment due to the suit configuration. Each IMU sensor is comprised of a three-axis accelerometer, a three-axis gyroscope, and a three-axis magnetometer. Motion data was transmitted between the suit and a laptop via Wi-Fi. The sensor locations are shown in Figure 13.

4.2.3 Experimental Procedure

In the bricklaying experiment, jerk analysis was carried out on five body segments, namely the pelvis, the dominant and non-dominant upper arms and thighs since lifts involve whole-body work. We hypothesized that the three distinct body segments are suitable for fatigue monitoring since bricklaying requires large ranges of motion, forceful contractions, high precision from the upper and lower limbs, and frequent bending at the torso. IMU sensors have been used to study human motion in several locations. However, some studies have found that the torso is the best location to analyze movements since it reflects major motions and is close to the human body center of mass [112]. The selected body segments may also be the most suitable areas for sensor placement since they are far from external impact and from subject protective equipment.

Prior to the experiment, a calibration session was carried out to allow the Axis Neuron software to detect the placement and orientation of the sensors on the participant. The sensor-to-segment calibration was obtained using three standard postures including the A-pose, T-pose, and S-pose. Two sets of analyses were conducted. First, we tested the feasibility of analyzing jerk values using continuous motion data to monitor changes in motor control with data collected from a previous study which required workers to complete a wall building experiment. Second, we conducted an additional experiment to evaluate changes in jerk values between two identical bricklaying tasks following a series of exhausting exercises. The participants were given an hour break between the two experiments.

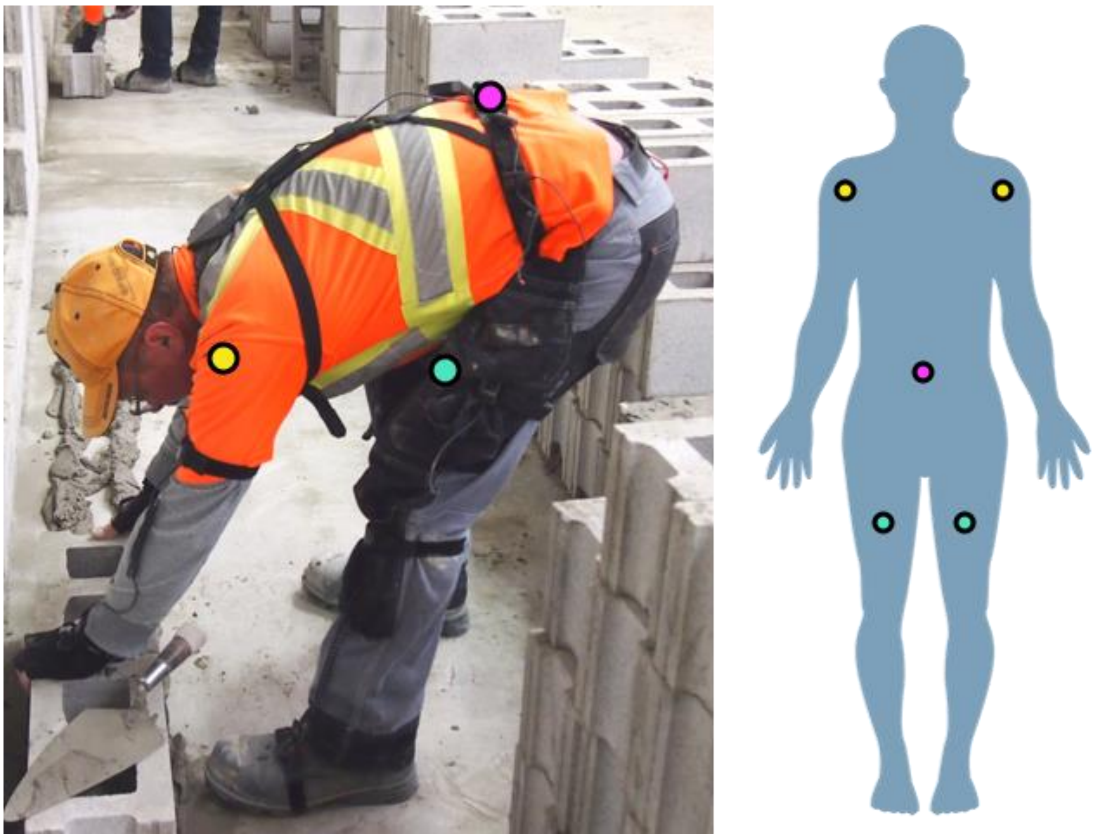

Figure 13 IMU sensor locations

4.2.4 Wall Building Experiment

To investigate the feasibility of using continuous motion data as an input to train SVM, we first analyzed data from our previous study [113]. Each participant was instructed to complete a pre-built lead wall shown in Figure 9(a), using forty-five concrete masonry units (CMUs) from the second to the sixth course. Each course is defined as a layer of CMUs. The CMUs were Type 1 blocks weighing 16.6 kg as detailed in Table 5. The blocks were placed in three piles approximately one meter away from the pre-built lead wall, and two panels of mortar were placed between the three block piles. The use of mortar and the requirement to meet alignment tolerances reflected field-work conditions. After the experiment, the participants were given a one-hour break before commencing the second experiment. Figure 15 shows the timeline of the tasks completed by the participants and the corresponding level of intensity measured in kg of laid CMU per minute.

Table 5 CMU block properties

Block	Weight [kg]	Dimensions [mm x mm x mm]
Type 1	16.6	390 x 190 x 100
Type 2	23.6	290 x 390 x 190
Type 3	36.1	290 x 390 x 190

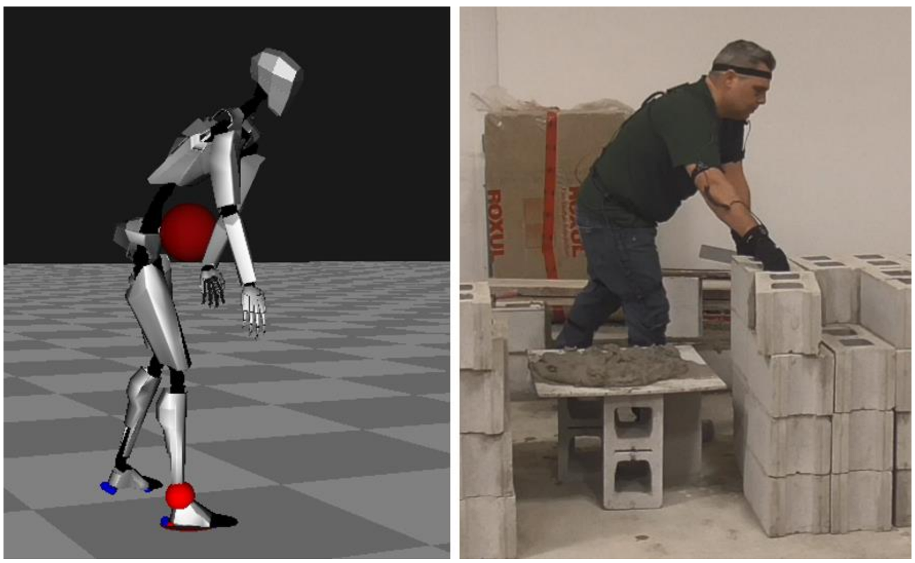

Figure 14 Human figure on Perception Neuron

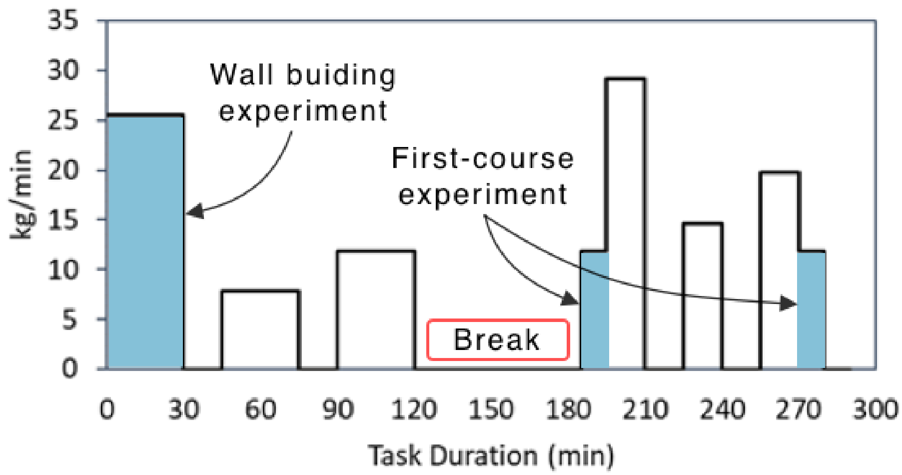

Figure 15 Timeline of task duration and intensity level in kilograms per minute

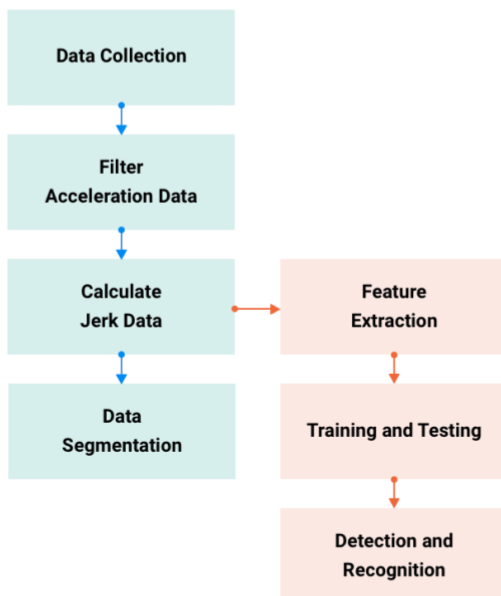

Figure 16 A schematic diagram of data processing for automatic fatigue detection

4.2.5 First Course Experiment

The purpose of the second experiment was to compare the jerk values of two identical tasks performed before and after an exhausting set of exercises. Each participant was instructed to build the first course of a wall using seven CMUs. The first course was selected because it imposes the greatest loading on the lower back [83]. The CMUs were Type 1 blocks weighing 16.6 kg. The blocks were placed in one pile approximately one meter away from the work space. Figure 17 shows a participant completing the bricklaying task.

After completing the first course, the participants were asked to carry out three bricklaying activities: 1) complete a wall individually using Type 2 CMUs, 2) complete a wall collaboratively using Type 2 CMUs, and 3) complete a wall collaboratively using Type 3 CMUs. In total, each participant carried approximately 1000 kg over an average of 50 minutes to complete all three bricklaying tasks. Lastly, the participants were asked to complete the first course again. Figure 18 and Figure 19 show the experiment sequence schematically.

Figure 17 Experimental setup for first course

Figure 18 Experimental setup for bricklaying task

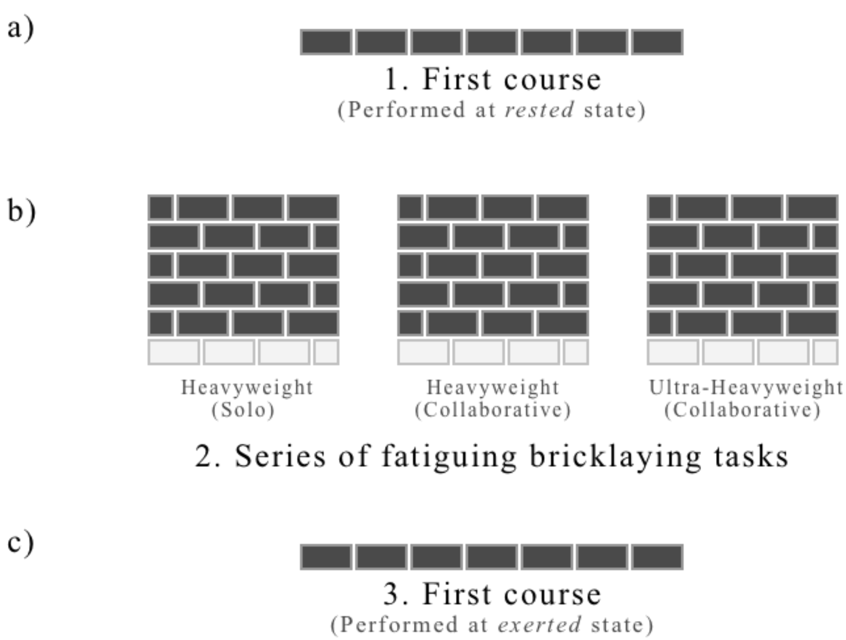

Figure 19 Building sequence for first course experiment

4.3 Data Processing

Body segment accelerations collected from the IMU accelerometers were imported into MATLAB for computations. Figure 16 shows the schematic diagram for the methodology used in machine learning following data pre-processing to bypass the requirement for manual task segmentation. For each of the five IMU sensors, the resultant acceleration data were calculated from the Cartesian components collected from the IMU accelerometers. High frequency noise was removed using a low-pass Butterworth filter with a 10Hz cut-off frequency. Jerk was calculated as the time-derivative of the acceleration magnitude as shown in Table 6.

The classification is performed using predefined MATLAB functions. SVM is a supervised learning algorithm for pattern recognition and classification. Given labelled training data, the algorithm outputs an optimal hyperplane that define decision boundaries which it can then use to categorize new data points. Linear, polynomial, and Gaussian kernels were employed in the SVM classifier. During the wall building experiment, the motion data collected during the second course was labelled as ‘rested’ and those collected during the sixth course was labelled as ‘exerted’. Likewise, during the first course experiment, the motion data collected during the first course completed at the beginning of the task was labelled as ‘rested’ and those collected at the end of the task was labelled as ‘exerted’.

Table 6 . Jerk calculations from Cartesian components of acceleration

	Formula
Acceleration	A_x, A_y, A_z
Resultant acceleration	$R = \sqrt{A_x^2 + A_y^2 + A_z^2}$
Resultant jerk	$J = \frac{dR}{dt}$
Jerk cost	$J = \int_{T_1}^{T_2} \left\lvert\frac{dR}{dt}\right\rvert^2 dt$

The selection of a window size has a significant impact on the classification accuracy. Wang et al. [114] conducted tests on different sliding-window sizes for activity recognition and found that accuracy decreases as window size increases. The optimal window size, however, is also dictated by what the classifier is required to classify such that the segment length is adequate to distinguish between unique signal patterns. Using a sliding window approach, multiple window sizes were tested and an overlap size of 50% was used. The window size for optimal recognition was 15 s. Features were extracted from the segmented data and characterized in both the time and frequency domains. The feature set was based solely on jerk measured in g/s and includes the following: 1) mean, the average value of acceleration data over the window; 2) standard deviation of acceleration values over the window; 3) maximum; 4) minimum; 5) jerk cost, an important measure to estimate the energy economy described by the area under squared jerk curve; and 6) dominant frequency – Fast Fourier Transform (FFT) over the window. The classification accuracies are based on all features and for all five body segments.

4.4 Results and Discussion

In our experiments of classifying rested and exerted states of six subjects, we considered jerk-based features extracted from five IMU sensor body locations, namely the pelvis, and dominant and non-dominant upper arms and thighs. In the classification stage, we applied several classifiers using MATLAB. On comparing the average classification accuracy, the analysis showed that the SVM classifiers had the highest average value for both experiments, as reported in Table 7 and Table 8. A five-fold cross-validation scheme was used to evaluate the SVM classification algorithms, providing an indication of how well the learner will do when the classifier is repeated using new data. Thus, the reported accuracy is the average accuracy over five iterations.

As expected, the SVM classification results demonstrated a significantly higher intra-subject rested/exerted classification than the inter-subject classification. For the wall completion experiment, the polynomial kernels (94%) performed better than the linear kernel (91%) to identify intra-subject rested/exerted states. For the first course experiment, the linear kernel performed similarly (80%) to the polynomial kernel (79%). The lower classifier accuracy for the first course experiment may be explained by the fact that it was completed following the first experiment. Since a sufficient amount of time is required for muscle recovery following exercise, the participants may not have fully recovered from the first experiment before moving onto the second experiment. Thus, the participants may have begun the second experiment in an exerted state. The participants might have also recruited an alternate group of muscles for the two collaborative lifting tasks compared to the individual lifting tasks during the first course experiment. Thus, fatigue may have built up for a different group of muscles that were not all used in laying the first courses. Another explanation could be that the level of intensity as measured in kilograms per minute could have affected the exertion levels developed by the participants. The intensity level was higher during the wall building experiment compared to the first course experiment; however, the series of fatiguing tasks conducted in between the two sets of first course block laying was higher in intensity.

Table 7 Wall completion experiment – SVM classification accuracy [%], mean, and standard deviation

SVM Kernel Function	Intra-subject							Inter-subject
	W1	W2	W3	W4	W5	W6	Mean±SD	All workers
Linear	98.0	84.1	87.0	91.1	84.6	100.0	90.8±6.8	78.5
Quadratic	98.0	87.0	89.1	95.6	94.2	100.0	**94.0±5.1**	79.2
Cubic	98.0	87.0	91.3	97.8	90.4	100.0	**94.1±5.2**	76.5
Fine Gaussian	62.7	69.6	58.7	66.7	63.5	56.7	63.0±4.8	60.1
Medium Gaussian	96.1	85.5	80.4	93.3	86.5	100.0	90.3±7.4	78.8
Course Gaussian	72.5	69.6	63.0	66.7	63.5	100.0	72.6±13.9	71.3

Table 8 First course experiment – SVM classification accuracy [%], mean, and standard deviation

SVM Kernel Function	Intra-subject							Inter-subject
	W1	W2	W3	W4	W5	W6	Mean±SD	All workers
Linear	75.4	74.0	69.1	76.6	84.6	100.0	**80.0±11.0**	62.0
Quadratic	72.3	71.4	68.1	76.6	87.2	97.1	78.8±11.2	63.0
Cubic	72.3	67.5	68.1	76.6	84.6	100.0	78.2±12.4	63.3
Fine Gaussian	52.3	59.7	61.7	51.9	56.4	60.0	57.0±4.2	57.6
Medium Gaussian	80.0	71.4	67.0	68.8	89.7	94.3	78.5±11.4	65.9
Course Gaussian	50.8	59.7	61.7	67.5	71.8	71.4	63.8±8.1	59.4

4.5 Limitations

Conclusions provided in this study should be considered in context of the limitations. First, there was no secondary measure of fatigue, thus we cannot be certain that experiments induced sufficient fatigue. Since we know that the participants had indeed exerted themselves in performing the bricklaying tasks, the classification accuracy reflects the extent to which fatigue was developed. Second, we did not consider masons with other experience levels other than expert masons. Third, due to the fact that physical exertion levels may last for several hours following physical activity, the break in between the first and second experiments may not have been sufficient for the participants to return to a rested state.

The placement of the sensors is of high importance because it can potentially affect the recognition between rested and fatigued states. Thus, future work should involve a feature selection method to identify the most significant motion changes after fatigue and determine the optimal number and placements of the sensors to improve the utility of the method.

4.6 Conclusion

In the construction industry, fatigue can impair workers ability to safely and effectively perform their duties which negatively impacts their well-being, reduces productivity and the quality of their work, and elevates workers' compensation costs. Current workload and fatigue assessment methods, including subjective, physiological, and biomechanical assessments, can be unreliable, cumbersome, or require extensive post processing, which render them impractical for real-time assessment.

This research investigated the use of SVMs to automatically recognize changes in jerk values due to physical exertion. Motion data were collected during two bricklaying activities using IMU sensors to obtain jerk input to SVM classifiers. Inter- and intra-subject classification of rested and exerted states of six expert masons were carried out using the jerk values of the pelvis, upper arms, and thighs.

We found that changes in jerk values due to the development of fatigue can be classified by supervised machine learning techniques. On average, intra-subject classification achieved an accuracy of 94% for the wall building experiment and 80% for the first course experiment. The difference between the classification accuracy for the two experiments may be attributed to differences in task sequence and intensity level resulting in lower classification accuracy in the first-course experiment compared to the wall experiment.

The results lead us to conclude that jerk changes resulting from exertion can be assessed by wearable sensors and SVMs. The investigated method holds promise for continuous monitoring of physical exertion and fatigue which can help in reducing work related musculoskeletal injuries or other fatigue-related risks.

Chapter 5 Conclusion and Recommendations

Physical fatigue is one of the factors leading to increased risk of injury, reduced productivity, and decline in work quality in the construction industry. Fatigue in musculature is associated with a decline in postural stability, motor performance, and altered normal motion patterns, leading to heightened risks of work-related musculoskeletal disorders. Physical fatigue has been previously demonstrated to be a good indicator of injury risks, thus, monitoring and detecting muscle fatigue during strenuous work may be advantageous in mitigating these risks. This research used wearable wireless inertial sensors and sought to evaluate the use of acceleration and its derivative, jerk, to detect changes in motor control using IMUs.

The objective of this thesis was to identify and evaluate jerk as a fatigue measure that is practical for both laboratory and in situ use. Through two studies, the thesis aimed to 1) evaluate the use of jerk to detect changes in motor control arising from physical exertion, 2) investigate differences in jerk values between motions performed by workers with varying skill levels, and 3) assess the suitability of machine learning techniques for real-time physical fatigue monitoring. Each of these objectives have been addressed as summarized in the following sections.

5.1 Jerk and Physical Fatigue

In our first study, we conducted bricklaying experiment with 32 male bricklayers with varying levels of masonry experience including novices, first-year apprentices, third-year apprentices, and journeymen. For each participant, a comparison between jerk values were made between the beginning and end of the bricklaying task to determine whether the participant had become more exerted over time. Among the experience groups, detectable differences between their rested and exerted states were seen only for the journeymen participants, indicating that they were physically exerted. Being physically exerted, however, did not affect their work pace as it remained relatively constant throughout the task. These results show that jerk may be a better, more sensitive, method for fatigue assessment in experienced workers where fatigue and productivity are not necessarily correlated. Since the design of the bricklaying experiment allowed self-pacing, inexpert workers including novices and apprentices, may have experienced lower levels of physical exertion and thus, insignificant changes in jerk values.

5.2 Jerk and Skill Level

Journeymen performed lifts with the lowest jerk values of all experience groups, demonstrating smooth motions and a high degree of motor control while maintaining high productivity. Novices and first-year apprentices appear to have greater motor control than third-year apprentices, however they have the lowest productivity. Moreover, they showed more caution toward risks of injury resulting in them moving with more controlled motions compared to the more experienced third-year apprentices. This observation supports the notion that individuals naturally adopt a preferred mode that are both self-selected and optimal with respect to variables such as work, time, energy, and physiological cost. In contrast, third-year apprentices performed lifts with the greatest jerk values, indicating inferior motor control. The productivity of third-year apprentices was also less than that of journeymen. The pressures to match production levels may have led third-year apprentices to use jerkier motions and greater effort than they may be physically prepared for.

5.3 In Situ Fatigue Detection using Machine Learning

In our second study, we investigated the use of support-vector machines (SVM) to automatically recognize jerk changes due to physical exertion. Previously in our first study, we noted the wide interpersonal variabilities in both jerk magnitude and change in jerk values between the participants' rested and fatigued states. Thus, it is essential to account for individual variabilities and allow for the establishment of individualized baseline conditions rather than a population condition. As such, we classified both inter-and intra-subject rested and exerted states for the pelvis, upper arms, and thigh. Classification results demonstrated a significantly higher intra-subject rested/exerted classification than the inter-subject classification. On average, intra-subject classification achieved an accuracy of 94% for the wall building experiment and 80% for the first course experiment. We conclude that jerk changes due to physical exertion can be detected using wearable sensors and SVMs.

5.4 Adequacy of Signal-to-Noise Ratio of IMU for Jerk Detection

The first study pilot experiment results suggest that the signal-to-noise ratio of jerk derived from IMU-based motion capture suits was high enough to detect differences between rested and exerted states. These results were confirmed by the findings in a bricklaying experiment which showed that jerk values for all journeymen's eleven body segments under study had sufficient signal-to-noise ratio to distinguish between rested and exerted states with a confidence level better than 99%. This finding, however, was not true for inexpert participants for the suspected reasons outlined in Section 6.1.

We hypothesized that spurious acceleration signals caused by contact and impact events between the hands and the CMUs, and the feet and ground, raised the noise floor of the acceleration signal, which were further amplified by the numerical differentiation to obtain jerk. Spurious acceleration signals diminish as they travel down along the kinematic chain extending from the hands to the pelvis. Thus, the signal-to-noise ratio improves for segments closer to the body center of mass.

5.5 Future Work and Recommendations

The recommended future area of work related to this research is the implementation and refinement of the experimental methodology. This is required for validating and improving this research. In addition, several areas of recommended research are proposed.

1) Additional research is required to improve sensing technologies particularly for environments that require dynamic work. While wearable motion sensor systems have been shown to exhibit good accuracy in both laboratory and in situ settings, their accuracy has been known to degrade when work activities involve complex and dynamic motions [115] or when measurements are taken in the presence of magnetically distorted fields [116]. Thus, a more robust hardware should be used to validate the results of the study.

2) Current estimation of physical demands is limited by the need for multiple sensors. Thus, future work involves a feature selection method to identify the most significant motion changes after fatigue and determine the optimal number and placements of the sensors to improve the utility of the method. Moreover, combining technologies and measurement methods capable of simultaneously capturing several processes of work would allow workers to move more naturally, thereby improving estimates of workplace exposure while reducing costs.

3) Currently, biomechanical and fatigue-related investigations have been restricted to analyses of brief periods of lifting and are assumed to represent those completed throughout an entire workday. However, several studies exploring motor recruitment patterns resulting from fatigue suggest that repetitive lifting over the course of an extended period may influence motor recruitment pattern and result in changes in the loading pattern on the body. Exploring the effect of fatigue during longer duration is expected to be more indicative of fatigue development and associated risks of injuries over a workday.

4) Lastly, research is required to establish jerk thresholds corresponding to fatigue and physical exertion levels that negatively impact workers' health, safety, productivity or work quality. This understanding would enable the development of warning systems against high levels of physical fatigue or as an indicator of recovery following fatigue. Moreover, it can guide enhancements made to the design of work schedules and systems to protect worker health and safety and maintain productivity and quality.

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Appendix A

MATLAB Scripts

I wish to acknowledge the help provided by my project teammate, Mohsen Diraneyya, in the generation of the data processing code.

Read_calc_file.m

```
%-------------------------------------------------------------------------%
% This function reads calculation files (.calc) exported from the Axis
% Neuron software following data collection using their IMU suit.
% This function reads the columns of interest including
% sensors locations, velocities, quaternions, accelerations and
% angular velocities for all 21 sensors in the calculation file.
% Note: some of them may be copies of each other, depending on the
% actual number of sensors used.
%-------------------------------------------------------------------------%

function [Calc_Data] = read_calc_file(calc_filename)

% add a file extension if necessary:
if ~strncmpi(fliplr(calc_filename),'calc.',5)
  calc_filename = [calc_filename,'.calc'];
end

%% counter for number of lines
fid=fopen(calc_filename,'r');
file_data_cell = textscan(fid, '%s',10000000,'delimiter', '\n');
file_data = file_data_cell{1,1};
no_of_raws=size(file_data_cell{1},1);

fclose(fid);

%% read line by line
Data=zeros(no_of_raws,338);
for i = 7 : no_of_raws
    tap_locations=strfind(file_data{i},'    ');
    Data(i,1)=str2double(file_data{i}(1:tap_locations(1)-1));
    for j=2:338
        Data(i,j)=str2double(file_data{i}(tap_locations(j-
1)+1:tap_locations(j)-1));
    end
end

Calc_Data=Data(7:end,:);
```

Kinematics_from_calc.m

```
%-----------------------------------------------------------------------%
% This function finds sensor locations, linear accelerations,
% angular velocities and angular accelerations from the .calc file
% Function outputs include sensors information for a 15-segment body model

% The order of the segments are as follows,
% 1: Pelvis, 2: Torso, 3: Head & Neck, 4: Right upper arm, 5: Right
% Forearm, 6: Right hand, 7: Left upper arm, 8: Left Forearm, 9: Left
% hand, 10: Right Thigh, 11: Right Shank, 12: Right Foot, 13: Left Thigh,
% 14: Left Shank and % 15: Left Foot

% All inputs from the .calc file are in "sensor global" frame except for
the location, the outputs are in the same frame except for location

% Note: The location inputs are in calculation BVH frame and location
% outputs are in 3D BVH frame (.bvh file) frame

% Note: CS = Coordinate System = Frame
%-----------------------------------------------------------------------%

function [A,omega,alpha,sensor_location] = Kinematics_from_calc(calc_data)

% Input: calc_data, contains the data as expressed in .calc file exported
% in sensor global CS,
% only numeric data starting from the first frame to the last frame, size:
% nx336, where n is the number of frames, 336 is 16 data elements for each
% of the 21 segments in .calc file.

% 16 data elements are in arranged in the following order:
% position x,y&z, velocity x,y&z, quaternion r,i,j&k, acceleration x,y&z
and angular velocity x,y&z

% The segments are as follows,
% 1: pelvis, 2: Right thigh, 3: right shank, 4: right foot, 5: left thigh,
% 6: left shank, 7: Left foot, 8: right shoulder, 9: right upper arm,
% 10: right forearm, 11: right hand, 12: left shoulder, 13: left upper
% arm,14: left forearm, 15: left hand, 16: head, 17: neck, 18: Spine3,
% 19: spine2, 20: spine1, 21: spine

% Note: 16 and 17 are exactly the same (copies) for quaternion,
acceleration and angular velocity
% Note: 18, 19 and 20 are exactly the same (copies) for quaternion,
acceleration and angular velocity
% Note: 1 and 21 are exactly the same (copies) for quaternion,
acceleration and angular velocity

% Outputs:
% A: sensor acceleration of each segment. 3xnx15 matrix, 3d vector for
each frame for each segment (meter per second squared)
```

```
% omega: angular velocity of each segment. 3xnx15 matrix, 3d vector for
each frame for each segment (per second squared)
% alpha: angular acceleration of each segment. 3xnx15 matrix, 3d vector
for each frame for each segment (per second)
%sensor_location: coordinates of each sensor's location in bvh CS, 3xnx15
matrix, 3d vector for each frame for each segment (meter),
% The coordinates are expressed away from zeta pelvis as the origin
(0,0,0)

%% read from calc_data matrix, and permute to fit the desired format
sensor_location_from_calc=zeros(size(calc_data,1),3,21);
A_from_calc=zeros(size(calc_data,1),3,21);
omega_from_calc=zeros(size(calc_data,1),3,21);
alpha_from_calc=zeros(size(calc_data,1)-1,3,21);

for i=0:20
    sensor_location_from_calc(:,1:3,i+1)=calc_data(:,16*i+1:16*i+3);
%segment i+1 sensor location
    A_from_calc(:,1:3,i+1)=calc_data(:,16*i+11:16*i+13)*9.81;
%segment i+1 acceleration in m/sec^2
    omega_from_calc(:,1:3,i+1)=calc_data(:,16*i+14:16*i+16);
%segment i+1 angular velocity in rad/sec
    alpha_from_calc(:,1:3,i+1)=diff(omega_from_calc(:,1:3,i+1))*121;
%segment i+1 angular acceleration in rad/sec^2 (differentiation of angular
velocity)
end

sensor_location_from_calc = permute(sensor_location_from_calc,[2,1,3]);
A_from_calc = permute(A_from_calc,[2,1,3]);
omega_from_calc = permute(omega_from_calc,[2,1,3]);
alpha_from_calc = permute(alpha_from_calc,[2,1,3]);

%% take only the segments we are interested in, in the order we are
interested in

R_sensor_BVH=[1 0 0;0 0 1;0 1 0]; %change reference frame from sensor
global to BVH
R_bvhcalc_BVH=[1 0 0; 0 0 -1; 0 1 0]; %change reference frame for sensor
location from bvh of .calc, to bvh of .3d

%1pelvis
sensor_location(:,:,1)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,1);
A(:,:,1)=R_sensor_BVH*A_from_calc(:,:,1);
omega(:,:,1)=R_sensor_BVH*omega_from_calc(:,:,1);
alpha(:,:,1)=R_sensor_BVH*alpha_from_calc(:,:,1);

%2Torso
sensor_location(:,:,2)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,18);
A(:,:,2)=R_sensor_BVH*A_from_calc(:,:,18);
omega(:,:,2)=R_sensor_BVH*omega_from_calc(:,:,18);
alpha(:,:,2)=R_sensor_BVH*alpha_from_calc(:,:,18);
```

```
%3head&neck
sensor_location(:,:,3)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,16);
A(:,:,3)=R_sensor_BVH*A_from_calc(:,:,16);
omega(:,:,3)=R_sensor_BVH*omega_from_calc(:,:,16);
alpha(:,:,3)=R_sensor_BVH*alpha_from_calc(:,:,16);

%4Right upperarm
sensor_location(:,:,4)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,9);
A(:,:,4)=R_sensor_BVH*A_from_calc(:,:,9);
omega(:,:,4)=R_sensor_BVH*omega_from_calc(:,:,9);
alpha(:,:,4)=R_sensor_BVH*alpha_from_calc(:,:,9);

%5Right forearm
sensor_location(:,:,5)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,10);
A(:,:,5)=R_sensor_BVH*A_from_calc(:,:,10);
omega(:,:,5)=R_sensor_BVH*omega_from_calc(:,:,10);
alpha(:,:,5)=R_sensor_BVH*alpha_from_calc(:,:,10);

%6Right hand
sensor_location(:,:,6)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,11);
A(:,:,6)=R_sensor_BVH*A_from_calc(:,:,11);
omega(:,:,6)=R_sensor_BVH*omega_from_calc(:,:,11);
alpha(:,:,6)=R_sensor_BVH*alpha_from_calc(:,:,11);

%7Left upperarm
sensor_location(:,:,7)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,13);
A(:,:,7)=R_sensor_BVH*A_from_calc(:,:,13);
omega(:,:,7)=R_sensor_BVH*omega_from_calc(:,:,13);
alpha(:,:,7)=R_sensor_BVH*alpha_from_calc(:,:,13);

%8Left forearm
sensor_location(:,:,8)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,14);
A(:,:,8)=R_sensor_BVH*A_from_calc(:,:,14);
omega(:,:,8)=R_sensor_BVH*omega_from_calc(:,:,14);
alpha(:,:,8)=R_sensor_BVH*alpha_from_calc(:,:,14);

%9Left hand
sensor_location(:,:,9)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,15);
A(:,:,9)=R_sensor_BVH*A_from_calc(:,:,15);
omega(:,:,9)=R_sensor_BVH*omega_from_calc(:,:,15);
alpha(:,:,9)=R_sensor_BVH*alpha_from_calc(:,:,15);

%10Right Thigh
sensor_location(:,:,10)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,2);
A(:,:,10)=R_sensor_BVH*A_from_calc(:,:,2);
omega(:,:,10)=R_sensor_BVH*omega_from_calc(:,:,2);
alpha(:,:,10)=R_sensor_BVH*alpha_from_calc(:,:,2);

%11Right Shank
sensor_location(:,:,11)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,3);
A(:,:,11)=R_sensor_BVH*A_from_calc(:,:,3);
omega(:,:,11)=R_sensor_BVH*omega_from_calc(:,:,3);
```

```
alpha(:,:,11)=R_sensor_BVH*alpha_from_calc(:,:,3);

%12Right foot
sensor_location(:,:,12)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,4);
A(:,:,12)=R_sensor_BVH*A_from_calc(:,:,4);
omega(:,:,12)=R_sensor_BVH*omega_from_calc(:,:,4);
alpha(:,:,12)=R_sensor_BVH*alpha_from_calc(:,:,4);

%13Left Thigh
sensor_location(:,:,13)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,5);
A(:,:,13)=R_sensor_BVH*A_from_calc(:,:,5);
omega(:,:,13)=R_sensor_BVH*omega_from_calc(:,:,5);
alpha(:,:,13)=R_sensor_BVH*alpha_from_calc(:,:,5);

%14Left Shank
sensor_location(:,:,14)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,6);
A(:,:,14)=R_sensor_BVH*A_from_calc(:,:,6);
omega(:,:,14)=R_sensor_BVH*omega_from_calc(:,:,6);
alpha(:,:,14)=R_sensor_BVH*alpha_from_calc(:,:,6);

%15Left foot
sensor_location(:,:,15)=R_bvhcalc_BVH*sensor_location_from_calc(:,:,7);
A(:,:,15)=R_sensor_BVH*A_from_calc(:,:,7);
omega(:,:,15)=R_sensor_BVH*omega_from_calc(:,:,7);
alpha(:,:,15)=R_sensor_BVH*alpha_from_calc(:,:,7);

% shift global origin to pelvis origin (assume same as sensor) for sensor
location. That is, now the sensor location is expressed away from the
pelvis origin, instead of global frame origin, however, the coordinates
are still in global frame.

for i=1:size(sensor_location,2)
    sensor_location(:,i,:)=sensor_location(:,i,:)-sensor_location(:,i,1);
end
```

Matrix_from_file.m

```
%-----------------------------------------------------------------------%
% Data processing: data filtering, acceleration from .calc file to jerk
%-----------------------------------------------------------------------%

function
[Matrix_pelvis,Matrix_DShoulder,Matrix_NShoulder,Matrix_DElbow,Matrix_NElb
ow,Matrix_DHip,Matrix_NHip,Matrix_D,Matrix_N,Matrix_All] =
matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc)

%% Inputs
Fs = 125; % Sampling frequency

%% import
[Calc_Data] = read_calc_file(File_Name);

Wn=Wc/62.5; %desired frequency is Wc, original frequency is 125
[b,a]=butter(2,Wn,'low'); %Butterworth filter factors
Calc_Data=filtfilt(b,a,Calc_Data); %Applying filter

[A,~,~,~] = Kinematics_from_calc(Calc_Data);

%% Calculating Jerk

% Acceleration magnitude
Pelvis_A=sqrt(sum(A(:,:,1).^2,1))';
RShoulder_A=sqrt(sum(A(:,:,4).^2,1))';
LShoulder_A=sqrt(sum(A(:,:,7).^2,1))';
RHip_A=sqrt(sum(A(:,:,10).^2,1))';
LHip_A=sqrt(sum(A(:,:,13).^2,1))';
RElbow_A=sqrt(sum(A(:,:,5).^2,1))';
LElbow_A=sqrt(sum(A(:,:,8).^2,1))';

%{
other segments
RWrist_A=sqrt(sum(A(:,:,6).^2,1))';
LWrist_A=sqrt(sum(A(:,:,9).^2,1))';
RKnee_A=sqrt(sum(A(:,:,11).^2,1))';
RAnkle_A=sqrt(sum(A(:,:,12).^2,1))';
LKnee_A=sqrt(sum(A(:,:,14).^2,1))';
LAnkle_A=sqrt(sum(A(:,:,15).^2,1))';
%}

% Jerk magnitude
Pelvis_J=diff(Pelvis_A)*125;
RShoulder_J=diff(RShoulder_A)*125;
LShoulder_J=diff(LShoulder_A)*125;
RHip_J=diff(RHip_A)*125;
LHip_L=diff(LHip_A)*125;
RElbow_J=diff(RElbow_A)*125;
```

```
LElbow_J=diff(LElbow_A)*125;

%{
other segments
RWrist_J=diff(RWrist_A)*125;
LWrist_J=diff(LWrist_A)*125;
RKnee_J=diff(RKnee_A)*125;
RAnkle_J=diff(RAnkle_A)*125;
LKnee_J=diff(LKnee_A)*125;
LAnkle_J=diff(LAnkle_A)*125;
%}

%% Calculating Selected Features values for each window
Window_frames=round(125*Window_size);
no_of_windows=floor(2*length(A)/Window_frames)-1;

%Features initiation
%pelvis
Pelvis_mean_J=zeros(no_of_windows,1);Pelvis_std_J=zeros(no_of_windows,1);
Pelvis_max_J=zeros(no_of_windows,1);Pelvis_min_J=zeros(no_of_windows,1);
Pelvis_JC=zeros(no_of_windows,1);Pelvis_peak_JF=zeros(no_of_windows,1);

%RShoulder
RShoulder_mean_J=zeros(no_of_windows,1);RShoulder_std_J=zeros(no_of_window
s,1);
RShoulder_max_J=zeros(no_of_windows,1);RShoulder_min_J=zeros(no_of_windows
,1);
RShoulder_JC=zeros(no_of_windows,1);RShoulder_peak_JF=zeros(no_of_windows,
1);

%LShoulder
LShoulder_mean_J=zeros(no_of_windows,1);LShoulder_std_J=zeros(no_of_window
s,1);
LShoulder_max_J=zeros(no_of_windows,1);LShoulder_min_J=zeros(no_of_windows
,1);
LShoulder_JC=zeros(no_of_windows,1);LShoulder_peak_JF=zeros(no_of_windows,
1);

%RElbow
RElbow_mean_J=zeros(no_of_windows,1);RElbow_std_J=zeros(no_of_windows,1);
RElbow_max_J=zeros(no_of_windows,1);RElbow_min_J=zeros(no_of_windows,1);
RElbow_JC=zeros(no_of_windows,1);RElbow_peak_JF=zeros(no_of_windows,1);

%LElbow
LElbow_mean_J=zeros(no_of_windows,1);LElbow_std_J=zeros(no_of_windows,1);
LElbow_max_J=zeros(no_of_windows,1);LElbow_min_J=zeros(no_of_windows,1);
LElbow_JC=zeros(no_of_windows,1);LElbow_peak_JF=zeros(no_of_windows,1);

%RHip
RHip_mean_J=zeros(no_of_windows,1);RHip_std_J=zeros(no_of_windows,1);
RHip_max_J=zeros(no_of_windows,1);RHip_min_J=zeros(no_of_windows,1);
RHip_JC=zeros(no_of_windows,1);RHip_peak_JF=zeros(no_of_windows,1);
```

```
%LHip
LHip_mean_J=zeros(no_of_windows,1);LHip_std_J=zeros(no_of_windows,1);
LHip_max_J=zeros(no_of_windows,1);LHip_min_J=zeros(no_of_windows,1);
LHip_JC=zeros(no_of_windows,1);LHip_peak_JF=zeros(no_of_windows,1);

for window = 1 : no_of_windows %jerk values during the window
  Window_Pelvis_J=Pelvis_J(floor(Window_frames*(window-
1)/2)+1:floor((Window_frames*(window-1)/2))+Window_frames);
  Window_RShoulder_J=RShoulder_J(floor(Window_frames*(window-
1)/2)+1:floor((Window_frames*(window-1)/2))+Window_frames);
  Window_LShoulder_J=LShoulder_J(floor(Window_frames*(window-
1)/2)+1:floor((Window_frames*(window-1)/2))+Window_frames);
  Window_RElbow_J=RElbow_J(floor(Window_frames*(window-
1)/2)+1:floor((Window_frames*(window-1)/2))+Window_frames);
  Window_LElbow_J=LElbow_J(floor(Window_frames*(window-
1)/2)+1:floor((Window_frames*(window-1)/2))+Window_frames);
  Window_RHip_J=RHip_J(floor(Window_frames*(window-
1)/2)+1:floor((Window_frames*(window-1)/2))+Window_frames);
  Window_LHip_J=LHip_L(floor(Window_frames*(window-
1)/2)+1:floor((Window_frames*(window-1)/2))+Window_frames);

  %Pelvis features
  Pelvis_mean_J(window)=  mean(Window_Pelvis_J);
  Pelvis_std_J(window)=  std(Window_Pelvis_J);
  Pelvis_max_J(window)=  max(Window_Pelvis_J);
  Pelvis_min_J(window)=  min(Window_Pelvis_J);
  Pelvis_JC(window)= sum(Window_Pelvis_J.^2)*(1/125);

  L = length(Window_Pelvis_J);
  Y = fft(Window_Pelvis_J);P2 = abs(Y/L);
  P1 = P2(1:floor(L/2)+1);P1(2:end-1) = 2*P1(2:end-1);
  f = Fs*(0:(L/2))/L;[~,max_location]=max(P1(2:end));
  Pelvis_peak_JF(window)=f(max_location+1);

  %RShoulder features
  RShoulder_mean_J(window)=  mean(Window_RShoulder_J);
  RShoulder_std_J(window)=  std(Window_RShoulder_J);
  RShoulder_max_J(window)=  max(Window_RShoulder_J);
  RShoulder_min_J(window)=  min(Window_RShoulder_J);
  RShoulder_JC(window)= sum(Window_RShoulder_J.^2)*(1/125);

  Y = fft(Window_RShoulder_J);P2 = abs(Y/L);
  P1 = P2(1:floor(L/2)+1);P1(2:end-1) = 2*P1(2:end-1);
  f = Fs*(0:(L/2))/L;[~,max_location]=max(P1(2:end));
  RShoulder_peak_JF(window)=f(max_location+1);

  %LShoulder features
  LShoulder_mean_J(window)=  mean(Window_LShoulder_J);
  LShoulder_std_J(window)=  std(Window_LShoulder_J);
  LShoulder_max_J(window)=  max(Window_LShoulder_J);
  LShoulder_min_J(window)=  min(Window_LShoulder_J);
```

```
LShoulder_JC(window)= sum(Window_LShoulder_J.^2)*(1/125);

Y = fft(Window_LShoulder_J);P2 = abs(Y/L);
P1 = P2(1:floor(L/2)+1);P1(2:end-1) = 2*P1(2:end-1);
f = Fs*(0:(L/2))/L;[~,max_location]=max(P1(2:end));
LShoulder_peak_JF(window)=f(max_location+1);

%REblow features
RElbow_mean_J(window)=  mean(Window_RElbow_J);
RElbow_std_J(window)=  std(Window_RElbow_J);
RElbow_max_J(window)=  max(Window_RElbow_J);
RElbow_min_J(window)=  min(Window_RElbow_J);
RElbow_JC(window)= sum(Window_RElbow_J.^2)*(1/125);

Y = fft(Window_RElbow_J);P2 = abs(Y/L);
P1 = P2(1:floor(L/2)+1);P1(2:end-1) = 2*P1(2:end-1);
f = Fs*(0:(L/2))/L;[~,max_location]=max(P1(2:end));
RElbow_peak_JF(window)=f(max_location+1);

%LElbow features
LElbow_mean_J(window)=  mean(Window_LElbow_J);
LElbow_std_J(window)=  std(Window_LElbow_J);
LElbow_max_J(window)=  max(Window_LElbow_J);
LElbow_min_J(window)=  min(Window_LElbow_J);
LElbow_JC(window)= sum(Window_LElbow_J.^2)*(1/125);

Y = fft(Window_LElbow_J);P2 = abs(Y/L);
P1 = P2(1:floor(L/2)+1);P1(2:end-1) = 2*P1(2:end-1);
f = Fs*(0:(L/2))/L;[~,max_location]=max(P1(2:end));
LElbow_peak_JF(window)=f(max_location+1);


%RHip features
RHip_mean_J(window)=  mean(Window_RHip_J);
RHip_std_J(window)=  std(Window_RHip_J);
RHip_max_J(window)=  max(Window_RHip_J);
RHip_min_J(window)=  min(Window_RHip_J);
RHip_JC(window)= sum(Window_RHip_J.^2)*(1/125);

Y = fft(Window_RHip_J);P2 = abs(Y/L);
P1 = P2(1:floor(L/2)+1);P1(2:end-1) = 2*P1(2:end-1);
f = Fs*(0:(L/2))/L;[~,max_location]=max(P1(2:end));
RHip_peak_JF(window)=f(max_location+1);

%LHip features
LHip_mean_J(window)=  mean(Window_LHip_J);
LHip_std_J(window)=  std(Window_LHip_J);
LHip_max_J(window)=  max(Window_LHip_J);
LHip_min_J(window)=  min(Window_LHip_J);
LHip_JC(window)= sum(Window_LHip_J.^2)*(1/125);
```

```
  Y = fft(Window_LHip_J);P2 = abs(Y/L);
  P1 = P2(1:floor(L/2)+1);P1(2:end-1) = 2*P1(2:end-1);
  f = Fs*(0:(L/2))/L;[~,max_location]=max(P1(2:end));
  LHip_peak_JF(window)=f(max_location+1);
end

%Label (0 non fatigued; 1 fatigued)
label=zeros(no_of_windows,1);
label(1:no_of_windows)=fatigued_state; %Non fatigued

if Dominant == 1
    DShoulder_mean_J=RShoulder_mean_J;
    DShoulder_std_J=RShoulder_std_J;
    DShoulder_max_J=RShoulder_max_J;
    DShoulder_min_J=RShoulder_min_J;
    DShoulder_JC=RShoulder_JC;
    DShoulder_peak_JF=RShoulder_peak_JF;

    NShoulder_mean_J=LShoulder_mean_J;
    NShoulder_std_J=LShoulder_std_J;
    NShoulder_max_J=LShoulder_max_J;
    NShoulder_min_J=LShoulder_min_J;
    NShoulder_JC=LShoulder_JC;
    NShoulder_peak_JF=LShoulder_peak_JF;

    DHip_mean_J=RHip_mean_J;
    DHip_std_J=RHip_std_J;
    DHip_max_J=RHip_max_J;
    DHip_min_J=RHip_min_J;
    DHip_JC=RHip_JC;
    DHip_peak_JF=RHip_peak_JF;

    NHip_mean_J=LHip_mean_J;
    NHip_std_J=LHip_std_J;
    NHip_max_J=LHip_max_J;
    NHip_min_J=LHip_min_J;
    NHip_JC=LHip_JC;
    NHip_peak_JF=LHip_peak_JF;

    DElbow_mean_J=RElbow_mean_J;
    DElbow_std_J=RElbow_std_J;
    DElbow_max_J=RElbow_max_J;
    DElbow_min_J=RElbow_min_J;
    DElbow_JC=RElbow_JC;
    DElbow_peak_JF=RElbow_peak_JF;

    NElbow_mean_J=LElbow_mean_J;
    NElbow_std_J=LElbow_std_J;
    NElbow_max_J=LElbow_max_J;
    NElbow_min_J=LElbow_min_J;
    NElbow_JC=LElbow_JC;
    NElbow_peak_JF=LElbow_peak_JF;
```

```matlab
else
    DShoulder_mean_J=LShoulder_mean_J;
    DShoulder_std_J=LShoulder_std_J;
    DShoulder_max_J=LShoulder_max_J;
    DShoulder_min_J=LShoulder_min_J;
    DShoulder_JC=LShoulder_JC;
    DShoulder_peak_JF=LShoulder_peak_JF;

    NShoulder_mean_J=RShoulder_mean_J;
    NShoulder_std_J=RShoulder_std_J;
    NShoulder_max_J=RShoulder_max_J;
    NShoulder_min_J=RShoulder_min_J;
    NShoulder_JC=RShoulder_JC;
    NShoulder_peak_JF=RShoulder_peak_JF;

    DHip_mean_J=LHip_mean_J;
    DHip_std_J=LHip_std_J;
    DHip_max_J=LHip_max_J;
    DHip_min_J=LHip_min_J;
    DHip_JC=LHip_JC;
    DHip_peak_JF=LHip_peak_JF;

    NHip_mean_J=RHip_mean_J;
    NHip_std_J=RHip_std_J;
    NHip_max_J=RHip_max_J;
    NHip_min_J=RHip_min_J;
    NHip_JC=RHip_JC;
    NHip_peak_JF=RHip_peak_JF;

    DElbow_mean_J=LElbow_mean_J;
    DElbow_std_J=LElbow_std_J;
    DElbow_max_J=LElbow_max_J;
    DElbow_min_J=LElbow_min_J;
    DElbow_JC=LElbow_JC;
    DElbow_peak_JF=LElbow_peak_JF;

    NElbow_mean_J=RElbow_mean_J;
    NElbow_std_J=RElbow_std_J;
    NElbow_max_J=RElbow_max_J;
    NElbow_min_J=RElbow_min_J;
    NElbow_JC=RElbow_JC;
    NElbow_peak_JF=RElbow_peak_JF;
end

%% Final Matrix
Matrix_pelvis=[Pelvis_mean_J,Pelvis_std_J,Pelvis_max_J,Pelvis_min_J,Pelvis
_JC,Pelvis_peak_JF,label];

Matrix_DShoulder=[DShoulder_mean_J,DShoulder_std_J,DShoulder_max_J,DShould
er_min_J,DShoulder_JC,DShoulder_peak_JF,label];
Matrix_NShoulder=[NShoulder_mean_J,NShoulder_std_J,NShoulder_max_J,NShould
er_min_J,NShoulder_JC,NShoulder_peak_JF,label];
```

```
Matrix_DElbow=[DElbow_mean_J,DElbow_std_J,DElbow_max_J,DElbow_min_J,DElbow
_JC,DElbow_peak_JF,label];
Matrix_NElbow=[NElbow_mean_J,NElbow_std_J,NElbow_max_J,NElbow_min_J,NElbow
_JC,NElbow_peak_JF,label];

Matrix_DHip=[DHip_mean_J,DHip_std_J,DHip_max_J,DHip_min_J,DHip_JC,DHip_pea
k_JF,label];
Matrix_NHip=[NHip_mean_J,NHip_std_J,NHip_max_J,NHip_min_J,NHip_JC,NHip_pea
k_JF,label];

Matrix_All=[Matrix_pelvis(:,1:end-1),Matrix_DShoulder(:,1:end-
1),Matrix_NShoulder(:,1:end-1),Matrix_DElbow(:,1:end-
1),Matrix_NElbow(:,1:end-1),Matrix_DHip(:,1:end-1),Matrix_NHip];
Matrix_D=[Matrix_pelvis(:,1:end-1),Matrix_DShoulder(:,1:end-
1),Matrix_DElbow(:,1:end-1),Matrix_DHip(:,1:end)];
Matrix_N=[Matrix_pelvis(:,1:end-1),Matrix_NShoulder(:,1:end-
1),Matrix_NElbow(:,1:end-1),Matrix_NHip(:,1:end)];
```

Prepare_all_data.m

```
%----------------------------------------------------------------------%
% Preparing body segment matrices for MATLAB classifiers from all workers
% Data_set_name,'Matrix_All','Matrix_pelvis','Matrix_DShoulder',
% 'Matrix_NShoulder','Matrix_DElbow','Matrix_NElbow','Matrix_DHip',
% 'Matrix_NHip','Matrix_D','Matrix_N'
%----------------------------------------------------------------------%

%%
Window_size=15;
Wc=10;

%% worker 3 non fatigued
File_Name='Worker3_nonfatigued_1.calc';
fatigued_state=0;
Dominant=1;

[Matrix_pelvis1,Matrix_DShoulder1,Matrix_NShoulder1,Matrix_DElbow1,Matrix_
NElbow1,Matrix_DHip1,Matrix_NHip1,Matrix_D1,Matrix_N1,Matrix_All1] =
matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 3 non fatigued
File_Name='Worker3_nonfatigued_2.calc';
fatigued_state=0;
Dominant=1;

[Matrix_pelvis2,Matrix_DShoulder2,Matrix_NShoulder2,Matrix_DElbow2,Matrix_
NElbow2,Matrix_DHip2,Matrix_NHip2,Matrix_D2,Matrix_N2,Matrix_All2] =
matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 4 fatigued
File_Name='Worker4_fatigued.calc';
fatigued_state=1;
Dominant=1;

[Matrix_pelvis3,Matrix_DShoulder3,Matrix_NShoulder3,Matrix_DElbow3,Matrix_
NElbow3,Matrix_DHip3,Matrix_NHip3,Matrix_D3,Matrix_N3,Matrix_All3] =
matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 4 non fatigued
File_Name='Worker4_nonfatigued.calc';
fatigued_state=0;
Dominant=1;

[Matrix_pelvis4,Matrix_DShoulder4,Matrix_NShoulder4,Matrix_DElbow4,Matrix_
NElbow4,Matrix_DHip4,Matrix_NHip4,Matrix_D4,Matrix_N4,Matrix_All4] =
matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 4 fatigued
File_Name='Worker4_fatigued.calc';
```

```
fatigued_state=1;
Dominant=1;

[Matrix_pelvis5,Matrix_DShoulder5,Matrix_NShoulder5,Matrix_DElbow5,Matrix_
NElbow5,Matrix_DHip5,Matrix_NHip5,Matrix_D5,Matrix_N5,Matrix_All5] =
matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 5 non fatigued
File_Name='Worker5_nonfatigued.calc';
fatigued_state=0;
Dominant=1;

[Matrix_pelvis6,Matrix_DShoulder6,Matrix_NShoulder6,Matrix_DElbow6,Matrix_
NElbow6,Matrix_DHip6,Matrix_NHip6,Matrix_D6,Matrix_N6,Matrix_All6] =
matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 5 fatigued
File_Name='Worker5_fatigued.calc';
fatigued_state=1;
Dominant=1;

[Matrix_pelvis7,Matrix_DShoulder7,Matrix_NShoulder7,Matrix_DElbow7,Matrix_
NElbow7,Matrix_DHip7,Matrix_NHip7,Matrix_D7,Matrix_N7,Matrix_All7] =
matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 6 non fatigued
File_Name='Worker6_nonfatigued.calc';
fatigued_state=0;
Dominant=1;

[Matrix_pelvis8,Matrix_DShoulder8,Matrix_NShoulder8,Matrix_DElbow8,Matrix_
NElbow8,Matrix_DHip8,Matrix_NHip8,Matrix_D8,Matrix_N8,Matrix_All8] =
matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 6 fatigued
File_Name='Worker6_fatigued.calc';
fatigued_state=1;
Dominant=1;

[Matrix_pelvis9,Matrix_DShoulder9,Matrix_NShoulder9,Matrix_DElbow9,Matrix_
NElbow9,Matrix_DHip9,Matrix_NHip9,Matrix_D9,Matrix_N9,Matrix_All9] =
matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 7 non fatigued
File_Name='Worker7_nonfatigued.calc';
fatigued_state=0;
Dominant=2;

[Matrix_pelvis10,Matrix_DShoulder10,Matrix_NShoulder10,Matrix_DElbow10,Mat
rix_NElbow10,Matrix_DHip10,Matrix_NHip10,Matrix_D10,Matrix_N10,Matrix_All1
0] = matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);
```

```
%% worker 7 fatigued
File_Name='Worker7_fatigued_1.calc';
fatigued_state=1;
Dominant=2;

[Matrix_pelvis11,Matrix_DShoulder11,Matrix_NShoulder11,Matrix_DElbow11,Mat
rix_NElbow11,Matrix_DHip11,Matrix_NHip11,Matrix_D11,Matrix_N11,Matrix_All1
1] = matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 8 fatigued
File_Name='Worker8_fatigued.calc';
fatigued_state=1;
Dominant=2;

[Matrix_pelvis12,Matrix_DShoulder12,Matrix_NShoulder12,Matrix_DElbow12,Mat
rix_NElbow12,Matrix_DHip12,Matrix_NHip12,Matrix_D12,Matrix_N12,Matrix_All1
2] = matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 8 non fatigued
File_Name='Worker8_nonfatigued.calc';
fatigued_state=0;
Dominant=1;

[Matrix_pelvis13,Matrix_DShoulder13,Matrix_NShoulder13,Matrix_DElbow13,Mat
rix_NElbow13,Matrix_DHip13,Matrix_NHip13,Matrix_D13,Matrix_N13,Matrix_All1
3] = matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);

%% worker 7 fatigued
File_Name='Worker7_fatigued_2.calc';
fatigued_state=1;
Dominant=1;

[Matrix_pelvis14,Matrix_DShoulder14,Matrix_NShoulder14,Matrix_DElbow14,Mat
rix_NElbow14,Matrix_DHip14,Matrix_NHip14,Matrix_D14,Matrix_N14,Matrix_All1
4] = matrix_from_file(File_Name,fatigued_state,Dominant,Window_size,Wc);


%% All Matrix
Matrix_pelvis=[Matrix_pelvis1;Matrix_pelvis2;Matrix_pelvis3;Matrix_pelvis4
;Matrix_pelvis5;Matrix_pelvis6;Matrix_pelvis7;Matrix_pelvis8;Matrix_pelvis
9;Matrix_pelvis10;Matrix_pelvis11;Matrix_pelvis12;Matrix_pelvis13;Matrix_p
elvis14];

Matrix_DShoulder=[Matrix_DShoulder1;Matrix_DShoulder2;Matrix_DShoulder3;Ma
trix_DShoulder4;Matrix_DShoulder5;Matrix_DShoulder6;Matrix_DShoulder7;Matr
ix_DShoulder8;Matrix_DShoulder9;Matrix_DShoulder10;Matrix_DShoulder11;Matr
ix_DShoulder12;Matrix_DShoulder13;Matrix_DShoulder14];

Matrix_NShoulder=[Matrix_NShoulder1;Matrix_NShoulder2;Matrix_NShoulder3;Ma
trix_NShoulder4;Matrix_NShoulder5;Matrix_NShoulder6;Matrix_NShoulder7;Matr
```

```
ix_NShoulder8;Matrix_NShoulder9;Matrix_NShoulder10;Matrix_NShoulder11;Matr
ix_NShoulder12;Matrix_NShoulder13;Matrix_NShoulder14];

Matrix_DElbow=[Matrix_DElbow1;Matrix_DElbow2;Matrix_DElbow3;Matrix_DElbow4
;Matrix_DElbow5;Matrix_DElbow6;Matrix_DElbow7;Matrix_DElbow8;Matrix_DElbow
9;Matrix_DElbow10;Matrix_DElbow11;Matrix_DElbow12;Matrix_DElbow13;Matrix_D
Elbow14];

Matrix_NElbow=[Matrix_NElbow1;Matrix_NElbow2;Matrix_NElbow3;Matrix_NElbow4
;Matrix_NElbow5;Matrix_NElbow6;Matrix_NElbow7;Matrix_NElbow8;Matrix_NElbow
9;Matrix_NElbow10;Matrix_NElbow11;Matrix_NElbow12;Matrix_NElbow13;Matrix_N
Elbow14];

Matrix_DHip=[Matrix_DHip1;Matrix_DHip2;Matrix_DHip3;Matrix_DHip4;Matrix_DH
ip5;Matrix_DHip6;Matrix_DHip7;Matrix_DHip8;Matrix_DHip9;Matrix_DHip10;Matr
ix_DHip11;Matrix_DHip12;Matrix_DHip13;Matrix_DHip14];

Matrix_NHip=[Matrix_NHip1;Matrix_NHip2;Matrix_NHip3;Matrix_NHip4;Matrix_NH
ip5;Matrix_NHip6;Matrix_NHip7;Matrix_NHip8;Matrix_NHip9;Matrix_NHip10;Matr
ix_NHip11;Matrix_NHip12;Matrix_NHip13;Matrix_NHip14];

Matrix_D=[Matrix_D1;Matrix_D2;Matrix_D3;Matrix_D4;Matrix_D5;Matrix_D6;Matr
ix_D7;Matrix_D8;Matrix_D9;Matrix_D10;Matrix_D11;Matrix_D12;Matrix_D13;Matr
ix_D14];

Matrix_N=[Matrix_N1;Matrix_N2;Matrix_N3;Matrix_N4;Matrix_N5;Matrix_N6;Matr
ix_N7;Matrix_N8;Matrix_N9;Matrix_N10;Matrix_N11;Matrix_N12;Matrix_N13;Matr
ix_N14];

Matrix_All=[Matrix_All1;Matrix_All2;Matrix_All3;Matrix_All4;Matrix_All5;Ma
trix_All6;Matrix_All7;Matrix_All8;Matrix_All9;Matrix_All10;Matrix_All11;Ma
trix_All12;Matrix_All13;Matrix_All14];

Data_set_name='Window15_Wc10';

save(Data_set_name,'Matrix_All','Matrix_pelvis','Matrix_DShoulder','Matrix
_NShoulder','Matrix_DElbow','Matrix_NElbow','Matrix_DHip','Matrix_NHip','M
atrix_D','Matrix_N')


%% worker 3
Matrix_pelvis=[Matrix_pelvis1;Matrix_pelvis2;Matrix_pelvis3];
Matrix_DShoulder=[Matrix_DShoulder1;Matrix_DShoulder2;Matrix_DShoulder3];
Matrix_NShoulder=[Matrix_NShoulder1;Matrix_NShoulder2;Matrix_NShoulder3];
Matrix_DElbow=[Matrix_DElbow1;Matrix_DElbow2;Matrix_DElbow3];
Matrix_NElbow=[Matrix_NElbow1;Matrix_NElbow2;Matrix_NElbow3];
Matrix_DHip=[Matrix_DHip1;Matrix_DHip2;Matrix_DHip3];
Matrix_NHip=[Matrix_NHip1;Matrix_NHip2;Matrix_NHip3];
Matrix_D=[Matrix_D1;Matrix_D2;Matrix_D3];
Matrix_N=[Matrix_N1;Matrix_N2;Matrix_N3];
Matrix_All=[Matrix_All1;Matrix_All2;Matrix_All3];
```

```
Data_set_name='Worker3_Window15_Wc10';

save(Data_set_name,'Matrix_All','Matrix_pelvis','Matrix_DShoulder','Matrix
_NShoulder','Matrix_DElbow','Matrix_NElbow','Matrix_DHip','Matrix_NHip','M
atrix_D','Matrix_N')

%% worker 4
Matrix_pelvis=[Matrix_pelvis4;Matrix_pelvis5];
Matrix_DShoulder=[Matrix_DShoulder4;Matrix_DShoulder5];
Matrix_NShoulder=[Matrix_NShoulder4;Matrix_NShoulder5];
Matrix_DElbow=[Matrix_DElbow4;Matrix_DElbow5];
Matrix_NElbow=[Matrix_NElbow4;Matrix_NElbow5];
Matrix_DHip=[Matrix_DHip4;Matrix_DHip5];
Matrix_NHip=[Matrix_NHip4;Matrix_NHip5];
Matrix_D=[Matrix_D4;Matrix_D5];
Matrix_N=[Matrix_N4;Matrix_N5];
Matrix_All=[Matrix_All4;Matrix_All5];

Data_set_name='Worker4_Window15_Wc10';

save(Data_set_name,'Matrix_All','Matrix_pelvis','Matrix_DShoulder','Matrix
_NShoulder','Matrix_DElbow','Matrix_NElbow','Matrix_DHip','Matrix_NHip','M
atrix_D','Matrix_N')

%% worker 5
Matrix_pelvis=[Matrix_pelvis6;Matrix_pelvis7];
Matrix_DShoulder=[Matrix_DShoulder6;Matrix_DShoulder7];
Matrix_NShoulder=[Matrix_NShoulder6;Matrix_NShoulder7];
Matrix_DElbow=[Matrix_DElbow6;Matrix_DElbow7];
Matrix_NElbow=[Matrix_NElbow6;Matrix_NElbow7];
Matrix_DHip=[Matrix_DHip6;Matrix_DHip7];
Matrix_NHip=[Matrix_NHip6;Matrix_NHip7];
Matrix_D=[Matrix_D6;Matrix_D7];
Matrix_N=[Matrix_N6;Matrix_N7];
Matrix_All=[Matrix_All6;Matrix_All7];

Data_set_name='Worker5_Window15_Wc10';

save(Data_set_name,'Matrix_All','Matrix_pelvis','Matrix_DShoulder','Matrix
_NShoulder','Matrix_DElbow','Matrix_NElbow','Matrix_DHip','Matrix_NHip','M
atrix_D','Matrix_N')

%% worker 6
Matrix_pelvis=[Matrix_pelvis8;Matrix_pelvis9];
Matrix_DShoulder=[Matrix_DShoulder8;Matrix_DShoulder9];
Matrix_NShoulder=[Matrix_NShoulder8;Matrix_NShoulder9];
Matrix_DElbow=[Matrix_DElbow8;Matrix_DElbow9];
Matrix_NElbow=[Matrix_NElbow8;Matrix_NElbow9];
```

```
Matrix_DHip=[Matrix_DHip8;Matrix_DHip9];
Matrix_NHip=[Matrix_NHip8;Matrix_NHip9];
Matrix_D=[Matrix_D8;Matrix_D9];
Matrix_N=[Matrix_N8;Matrix_N9];
Matrix_All=[Matrix_All8;Matrix_All9];

Data_set_name='Worker6_Window15_Wc10';

save(Data_set_name,'Matrix_All','Matrix_pelvis','Matrix_DShoulder','Matrix
_NShoulder','Matrix_DElbow','Matrix_NElbow','Matrix_DHip','Matrix_NHip','M
atrix_D','Matrix_N')

%% worker 7
Matrix_pelvis=[Matrix_pelvis10;Matrix_pelvis11;Matrix_pelvis12];
Matrix_DShoulder=[Matrix_DShoulder10;Matrix_DShoulder11;Matrix_DShoulder12
];
Matrix_NShoulder=[Matrix_NShoulder10;Matrix_NShoulder11;Matrix_NShoulder12
];
Matrix_DElbow=[Matrix_DElbow10;Matrix_DElbow11;Matrix_DElbow12];
Matrix_NElbow=[Matrix_NElbow10;Matrix_NElbow11;Matrix_NElbow12];
Matrix_DHip=[Matrix_DHip10;Matrix_DHip11;Matrix_DHip12];
Matrix_NHip=[Matrix_NHip10;Matrix_NHip11;Matrix_NHip12];
Matrix_D=[Matrix_D10;Matrix_D11;Matrix_D12];
Matrix_N=[Matrix_N10;Matrix_N11;Matrix_N12];
Matrix_All=[Matrix_All10;Matrix_All11;Matrix_All12];

Data_set_name='Worker7_Window15_Wc10';

save(Data_set_name,'Matrix_All','Matrix_pelvis','Matrix_DShoulder','Matrix
_NShoulder','Matrix_DElbow','Matrix_NElbow','Matrix_DHip','Matrix_NHip','M
atrix_D','Matrix_N')

%% worker 8
Matrix_pelvis=[Matrix_pelvis13;Matrix_pelvis14];Matrix_DShoulder=[Matrix_D
Shoulder13;Matrix_DShoulder14];
Matrix_NShoulder=[Matrix_NShoulder13;Matrix_NShoulder14];
Matrix_DElbow=[Matrix_DElbow13;Matrix_DElbow14];
Matrix_NElbow=[Matrix_NElbow13;Matrix_NElbow14];
Matrix_DHip=[Matrix_DHip13;Matrix_DHip14];
Matrix_NHip=[Matrix_NHip13;Matrix_NHip14];
Matrix_D=[Matrix_D13;Matrix_D14];
Matrix_N=[Matrix_N13;Matrix_N14];
Matrix_All=[Matrix_All13;Matrix_All14];

Data_set_name='Worker8_Window15_Wc10';

save(Data_set_name,'Matrix_All','Matrix_pelvis','Matrix_DShoulder','Matrix
_NShoulder','Matrix_DElbow','Matrix_NElbow','Matrix_DHip','Matrix_NHip','M
atrix_D','Matrix_N'
```