Automated Monitoring of Physical Fatigue Using Jerk

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Abstract –

Construction workers are commonly subjected to ergonomic risks due to manual material handling that requires high levels of energy input over long work hours. Fatigue in musculature is associated with 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. Currently, few researchers have investigated how physical fatigue and exertion can be continuously monitored for practical use outside laboratory settings. Exercise-induced fatigue has been shown to impact motor control; thus, it can be measured using jerk, the time derivative of acceleration. This paper investigates the application of a machine learning approach, Support Vector Machine (SVM), to automatically recognize jerk changes due to physical exertion. We hypothesized that physical exertion and fatigue will influence motions and thus, can be classified based on jerk values. The motion data of six expert masons were collected using IMU sensors during two bricklaying tasks. The pelvis, upper arms, and thighs jerk values were used to classify inter- and intra-subject rested and exerted states. Our results show that on average, intra-subject classification achieved an accuracy of 94% for a five-course wall building experiment and 80% for a first-course experiment, leading us to conclude that jerk changes due to physical exertion can be detected using wearable sensors and SVMs.

Keywords –

Fatigue; Masonry; Classification; Lifting; Jerk

1 Introduction

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 require 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 recent advances of inertial measurement units (IMUs) enable the automatic collection of motion data and 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.

2 Background

Physical fatigue refers to a decline in a muscle's ability to exert force as a result of performing a task requiring physical effort [1], [2]. Physical fatigue has been shown to result in increased risks of injury that lead to a variety of musculoskeletal disorders including lower back disorders, tendinitis, and carpal tunnel syndrome [3].

Construction work typically involves prolonged hours of physically demanding tasks, such that workers' muscles can become fatigued, resulting in a reduction in muscle strength.

Currently, there is no standard for a fatigue assessment that is universally accepted in both practical or research settings [4]. Thus, numerous objective and subjective fatigue assessments have been developed for specific industry requirement such as construction, manufacturing, and healthcare. Several work-related studies have developed or used various subjective scales and questionnaires for assessing fatigue or perceived exertion [5]–[7]. Aside from the inherent discrepancies that is expected between one's perceived fatigue and one's true level of fatigue, subjective measures are also cumbersome to implement and are not realistic for use on construction sites [8].

Previous studies have also used physiological measurements to assess the buildup of fatigue, including heart rate, oxygen consumption, and energy expenditure [9]. The downside to physiological measurements is that many factors can reduce their reliability including alcohol consumption, fitness level, and caffeine intake [10]. In laboratory settings, electromyography (EMG) is commonly used to predict muscle activity. Surface EMG (sEMG) can non-invasively assess the development of fatigue over time, however, it has low signal-to-noise ratio and are poorly correlated to fatigue for deep muscles such as at the lower back [11]–[13].

Recent advancements of wearable sensors with processing and communication capabilities, have expanded the applications of existing assessments beyond laboratory settings. 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 [14]. 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 [15]–[18]. Among inertial sensors, accelerometers have been used extensively for activity recognition and studied with different body locations, number of sensors, classifiers, and feature sets [19]. Valero et al. developed an IMU system to detect unsafe postures of construction workers from motion data [20]. Ryu et al. used a single wrist-worn accelerometer-embedded activity tracker for automated action recognition [21], [22]. However, the use of wearable sensors to monitor physical exertion or fatigue during physically demanding tasks has not been studied extensively.

Physical fatigue and its impact on motor control and jerk has not been widely studied outside of clinical research. One reason is because prior to the advent of IMUs, motion capture systems that collect body segment positions must be differentiated three times in order to obtain jerk, resulting in a low signal-to-noise ratio. Jerk, the time derivative of acceleration, is typically used as a measure of motor control. In the short-term, fatigue can result in reduced motor control and strength capacity [23]. Fatigue is also manifested in increased tremor and changes in the recruitment of muscles, affecting both gross and fine motor skills. During lifting, high jerk values or a sudden change in acceleration can be felt as the change in force on the body and result in biomechanical damages over time. 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 [24]. Similarly, Zhang et al. used support vector machines (SVMs) to classify the occurrence of lower extremity muscle fatigue of gait [25]. These methods, however, have not assessed the feasibility of using machine learning techniques to recognize changes in jerk values during construction work.

Several methods have been used 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.

In our previous work [26], 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 paper, 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 [17], [27]. 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.

3   Methodology

3.1   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.

3.2   Instrumentation

The segment kinematics of the participants were collected using a wearable IMU-based motion capture suit, Noitom Perception Neuron [28]. 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 1.

3.3   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 [29]. 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 1. IMU sensor locations

3.4   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 [26]. Each participant was instructed to complete a pre-built lead wall shown in Figure 2(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 1. 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 3 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 1. CMU block properties

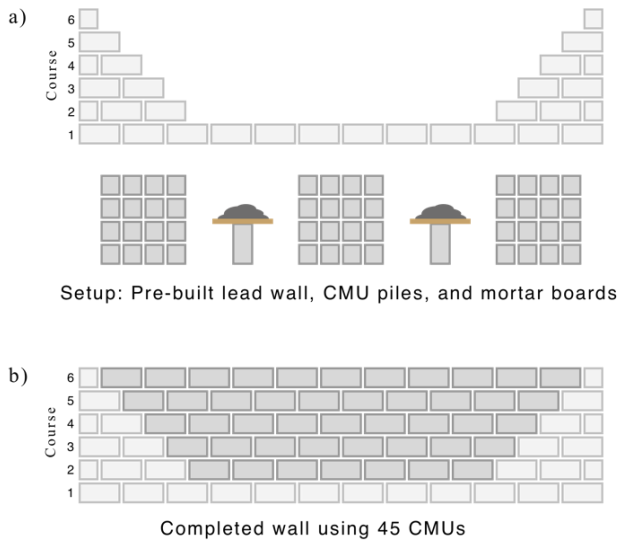| Block	Weight [kg]	Dimensions [mm x mm x mm]
Type 1	16.6	390 x 190 x 100
Type 2	23.6	290 x 390 x 190
Type 3	36.1	290 x 390 x 190

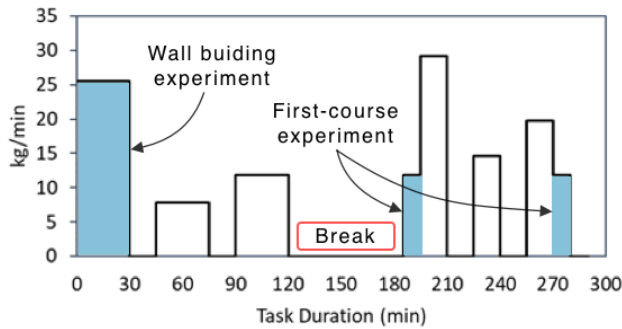Figure 2. Experimental setup for wall building experiment

Figure 3. Timeline of task duration and intensity level in kilograms per minute

3.5 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 [30]. 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 4 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 5 shows the experiment sequence schematically.
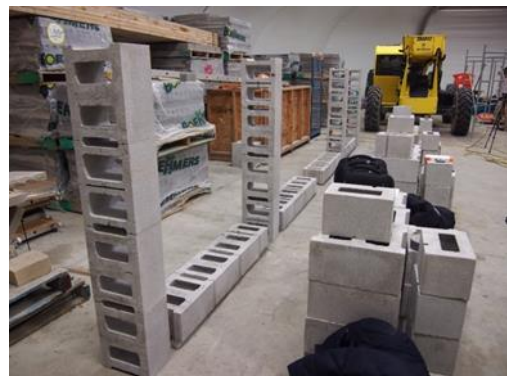

Figure 4. Experimental setup for first course (top) and series of exhausting bricklaying tasks (bottom)
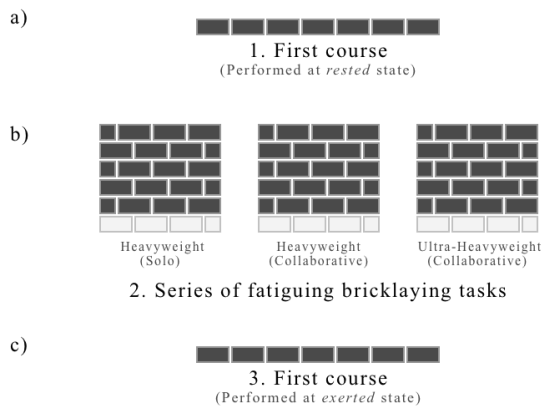
Figure 5. Building sequence for first course experiment

4 Data Analysis

Body segment accelerations collected from the IMU accelerometers were imported into MATLAB for computations. 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 2.

Table 2. 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	$J = \dfrac{dR}{dt}$
Jerk cost	$J = \displaystyle\int_{T_1}^{T_2} \left| \dfrac{dR}{dt} \right|^2 dt$

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'. Figure 6 shows the schematic to bypass the requirement for manual task segmentation.
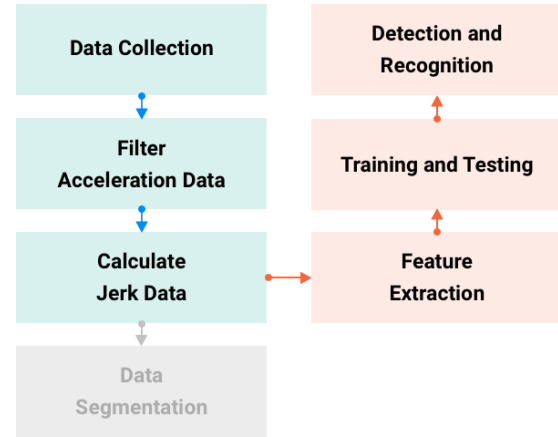

Figure 6. A schematic diagram of data processing for automatic fatigue detection

The selection of a window size has a significant impact on the classification accuracy. Wang et al. [31] 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 characterised 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.

5 Results & 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 3 and Table 4. 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 it 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

Table 3. 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 4. 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

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 utilized 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.

6 Limitations and Future Work

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 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.

7 Conclusions

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.

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