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Lichen Zhang
University of Waterloo


Mohsen Diraneyya
University of Waterloo


Juhyeong Ryu
University of Waterloo


Carl Haas
University of Waterloo

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# ASSESSMENT OF JERK AS A METHOD OF PHYSICAL FATIGUE DETECTION

**Lichen Zhang**
University of Waterloo
Waterloo, Ontario, Canada

**Mohsen Mutasem Diraneyya**
University of Waterloo
Waterloo, Ontario, Canada

**JuHyeong Ryu**
University of Waterloo
Waterloo, Ontario, Canada

**Carl T. Haas**
University of Waterloo
Waterloo, Ontario, Canada

**Eihab Abdel-Rahman**
University of Waterloo
Waterloo, Ontario, Canada

## ABSTRACT

Workers' fatigue is a significant problem in physically demanding occupations. Physical fatigue is known to result in the inability to maintain proper posture and working technique. Consequently, workers lose their ability to safely and effectively perform their duties. Thus, understanding the physical demands of labor-intensive work is of great importance in protecting workers' safety, and maintaining productivity. Current fatigue assessments methods, including surveys and questionnaires, are subjective and lack reliability. Objective fatigue assessments based on physiological data are more reliable, however they are cumbersome to implement in real work conditions. There is a need for an objective fatigue assessment method that can monitor physical fatigue with minimal intrusion. The goal of this study was to investigate whether jerk, the time-derivative of acceleration, can be used to objectively detect physical fatigue. A pilot study on masons was conducted to determine if physical fatigue can be detected by changes in jerk values. Ten participants performed a bricklaying task using forty-five concrete masonry units (CMU). Seven body segments, namely the hands, forearms, upper arms, and pelvis, were selected for placement of IMU sensors to measure the segment accelerations. Jerk was calculated from the measured acceleration via numerical differentiation. Characteristic values of the jerk at the beginning and end of the bricklaying task were obtained to represent the rested and fatigued states. They were then compared for significant differences. Jerk values calculated from the IMU sensors located on the upper arms and pelvis showed significant differences between rested and fatigued states. The results of this pilot study indicate that the characteristic jerk can be used to detect physical fatigue, however caution must be taken in selecting sensor locations to reduce the influence of spurious signals.

## INTRODUCTION

Physical fatigue is defined as a decrease in the ability to generate force due to vigorous and or sustained physical activity. Physical fatigue may lead to short-term outcomes such as increased risk of accidents, and long-term adverse outcomes such as chronic fatigue syndrome, burnout syndrome, and increased risk of ergonomic hazards such as work-related musculoskeletal disorders (WMSD) [1]. The adverse effects of fatigue on workers' safety, health, and productivity is widely accepted, however, there is no consensus on quantitative techniques used to assess fatigue levels or establish acceptable limits. The human body also exhibits physical fatigue in several ways. Consequently, researchers have approached the detection of physical fatigue and measure of physical demands in a multitude of ways. Due to the lack of a gold standard for fatigue measurement, assessments are usually tailored to the task in which fatigue is being studied [2]. Thus, there is a clear need for objective fatigue assessments that can be easily implemented for a variety of work tasks. Understanding worker fatigue and task demands will aid the development of improved work procedures and methods, and adjustments to work-rest cycles and work expectations.

Fatigue can be measured using objective or subjective assessment methods. Objective measures of fatigue focus on physiological processes and subjective measures focus on self-report assessments. Previous studies on fatigue measurement commonly use subjective measures including questionnaires or surveys. Self-report assessments have been shown to be highly variable between workers of different ethnic and socioeconomic backgrounds who have their own definitions and experiences of fatigue [3]. To overcome the limitations of self-report assessments concerned with their degree of accuracy and reliability, many researchers measure physiological processes. These processes include heart rate, oxygen consumption, EMG activity, and energy expenditure. However, they are often cumbersome and impractical to implement in real work conditions. Moreover, physiological and behavioral factors such as age, physical fitness, body weight, and smoking habits have also been found to significantly influence changes in physiological processes [4]. An alternative to objective measures of fatigue based on physiological processes is to use kinematic data collected by motion capture systems.

Optoelectronic measurement systems are accepted as gold-standards for non-invasive analysis of body motion within research settings. However, these systems are costly, require a large installation space, and require extensive post-processing. They are also cumbersome to the wearer and may inhibit natural motion. The recent development of inertial measurement units (IMUs) enable the automatic and continuous collection of whole body motion data. IMUs integrate accelerometers, magnetometers and gyroscopes sensors to measure acceleration, velocity, and orientation of body segments. Wearable IMU-based motion sensors are wireless, non-intrusive, versatile, and less costly compared to other methods of motion tracking and provide a more plausible solution for body motion capture. Thus, IMU-based sensors have high potential to be used as a field-based fatigue assessment method.

The authors propose the use of IMU-based sensors to objectively measure physical fatigue. Physical fatigue has been linked to a reduction in motor control which is commonly assessed using a jerk metric. Based on the kinematic data collected by the IMUs, jerk, the first time-derivative of acceleration, can be conveniently calculated. Jerk is often used in the medical field to assess motor control and motion smoothness and differentiate between healthy and pathological people suffering from diseases such as low back pain, stroke, and Parkinson's disease. However, jerk metrics have not been widely studied in occupational settings to detect motor control impairments due to physical fatigue. Moreover, only few studies have examined the feasibility of using IMU-based sensors to detect changes in jerk values from a rested to a fatigued state. Therefore, this study aims to investigate the feasibility of using a jerk assessment based on kinematic data to objectively detect physical fatigue. To test the feasibility, the authors conducted a pilot study on indoor masonry work that involve physically demanding tasks. In the test, motion data was collected from ten participants completing a bricklaying task using IMU-based motion capture suits.

## LITERATURE REVIEW

### *Motion Smoothness and Physical Fatigue*

Fatigue is a contributing factor to diminished motor control, reduced strength capacity, decreased productivity, poor quality of work, and loss of motivation and attentiveness [5]. Repetitive lifting has been found to lead to muscular fatigue and, hence, reduced motor performance and motor control. This is expected to increase loads on the low back and result in injury [6]. Thus, metrics used to assess motor control have the potential to be used to assess physical fatigue.

Motion smoothness is a characteristic of healthy and well-performed movements [7]. In literature, motion smoothness metrics are used to assess motor performance and control. Motion smoothness metrics are based on kinematic data such as number of peaks in the velocity profile, ratio between the maximum and the mean velocity during the movement, [8] and jerk [9]. Van Dieën et al. examined if fatigue affects the execution of repetitive lifting of a barbell using an optoelectronic system. The mean squared jerk at each joint was used as an indicator of motion smoothness. It was found that the group averages of jerk increased in all joints including the ankle, knee, hip, and lumbosacral joint. This was attributed to the change in the timing of muscle activation in the presence of fatigue to maintain pace [10]. Maman et al. examined the use of wearable sensors to detect physical fatigue occurrence in simulated manufacturing tasks. Predictive features of fatigue, which included wrists and hip jerk, were found to be strongly indicative of participants experiencing physical fatigue [1]. These fatigue assessment studies required their participants to complete tasks using a particular technique and at a predetermined pace. This would likely lead to the neglect of sub-movements performed in real work conditions and result in an inaccurate representation of worker behavior and the task.

### *Case Study on Masonry Work*

In the construction industry, physical fatigue is an occupational hazard as it increases the incidences of injuries and accidents at the workplace. Among construction trades, masonry work involves a number of repeated manual lifting with heavy materials. The job duties of bricklayers require them to work in awkward and repetitive postures, prolonged hours, and in harsh on-site condition. Thus, bricklayers may suffer from physical fatigue which results in increased risks of injury. The Construction Safety Association of Ontario [11] found that 62% of over-exertion injuries among bricklayers are back injuries, with an additional 35% being upper extremity injuries. Consequently, this paper focuses on the upper body and trunk motion during a bricklaying task. With the advent of wireless IMUs, it has become possible to continuously collect the motion data required for fatigue assessment in real work conditions. Thus, a pilot study on masonry work was conducted to evaluate the feasibility of using IMU-based sensors or other wireless accelerometers to detect physical fatigue.

## METHODS

### *Bricklaying Task*

The experiment was conducted at the Canadian Masonry Design Center (CMDC) in Mississauga, Ontario in an indoor facility. Ten male bricklayers with varying levels of experience were recruited. Each participant was instructed to complete a pre-built lead wall using forty-five concrete masonry units (CMUs), Figure 1. The CMUs were Type "A" concrete units, each weighing 16.6 kg with dimensions of 390 x 190 x 100 mm.

The entire bricklaying task consisted of forty-five lifts. Each 'lift' consists of the lifting, moving, and laying down of a CMU. The participants were instructed to complete the task as they do on a worksite. The CMUs were placed in three piles approximately one meter away from the lead wall. Two panels of mortar were positioned between the three pallets. Figure 2 shows the experimental layout and a participant completing the bricklaying task.

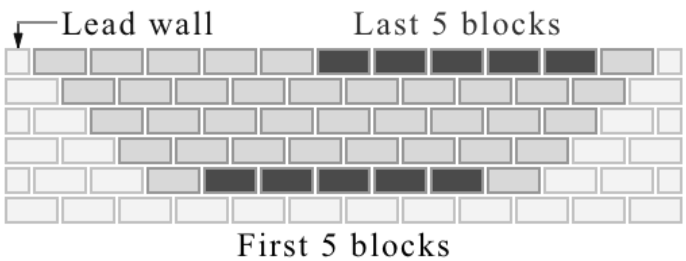


**FIGURE 1. PRE-BUILT LEAD WALL TO BE COMPLETED FROM SECOND TO SIXTH COURSE**

**FIGURE 2. COMPLETION OF LEAD WALL BY PARTICIPANT**

### *Instrumentation*

The full-body kinematics of the participants were collected using wireless IMU-based motion capture suits, Perception Neuron [12] for the duration of the bricklaying task. The suit is composed of seventeen IMU sensors, each comprised of a three-axis accelerometer, three-axis gyroscope, and three-axis magnetometer. The sampling rate is set to 125 frames per second. Two camcorders were used to capture the task on video. The videos were only used to segment the lifting activities in the data processing phase.

### *Motion Data Collection and Data Processing*

The motion suits were calibrated to each participant before commencing with his task. The participants used an alignment wire to help align the courses during the task. Motion and video data were collected continuously until the wall was completed. Following the experiment, the motion data collected from the IMU suits were exported as calculation (.calc) files containing the angular velocity and linear acceleration of all body segments over the duration of the bricklaying task. The calculation files were segmented to individual lifts and converted to .mat files for data processing.

Seven body segments, namely the hands, forearms, upper arms, and pelvis, were selected for jerk analysis. It was hypothesized that segments of the upper limbs would be suitable for fatigue detection since bricklaying requires larger motions, more forceful contractions, and higher precision from the upper limbs. The pelvis was selected due to frequent torso bending which may result in lower back muscle fatigue. Alwasel et al. found that bricklaying tasks result in elevated muscle activity in the upper limbs but does not change the lower limbs motions significantly over the duration of the task [13]. Thus, the pelvis and upper limb segments were hypothesized to provide the best targets for fatigue detection.

The magnitude of each body segment acceleration was calculated from its Cartesian components listed in the calculation file. The resultant acceleration was filtered using a low-pass Butterworth filter with a 10 Hz cut-off frequency to remove high frequency noise. Jerk was calculated as the time-derivative of the acceleration magnitude. The jerk of the dominant hand, forearm, upper arm, and pelvis are shown in Figure 3 as functions of time during the first and last lifts completed by one participant.

The jerk was averaged during the first five lifts of the bricklaying task to represent each participant's characteristic jerk in 'rested' state $J_r$ and during last five lifts to represent the characteristic jerk in 'fatigued' state $J_f$. The first and last five blocks laid during those lifts are shown in Figure 1. The average jerk values of the rested and fatigued states were then compared.

## RESULTS AND DISCUSSION

For each of the seven candidate body segments, the mean and standard deviation of the characteristic jerk values $J_r$ and $J_f$ of the ten participants were calculated. In addition, unpaired t-test (two-sided, $p < 0.05$) was deployed to compare among the characteristic jerk values $J_r$ and $J_f$ of the ten participants. Table 1 lists the computed mean, standard deviation, and $p$-value for each of the seven segments.

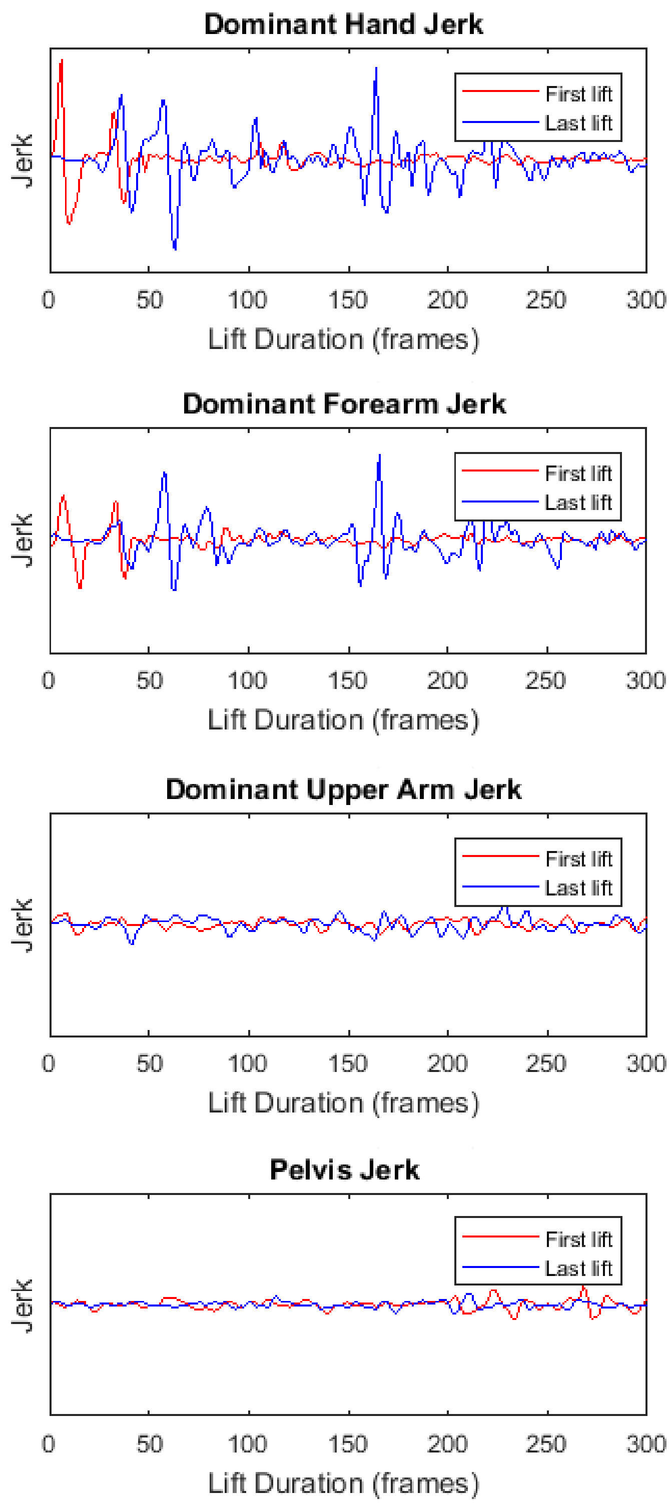


**FIGURE 3. SAMPLE JERK VALUES DURING THE FIRST AND LAST LIFTS**

The results show an increase in the mean jerk between the first five $(J_r)_{Ave}$ and last five $(J_f)_{Ave}$ lifts for all seven body segments. This indicates that a detectable difference exists between jerk in rested and fatigued states. However, two out of the ten participants showed a decrease in the characteristic jerk of the fatigued state compared to the characteristic jerk of the rested state. This may be due to variation in the physical conditioning of the participants. It is hypothesized that the bricklaying task did not induce fatigue in those participants.

The differences between the characteristic jerk of rested and fatigued states were significant for the dominant ($p < 0.043$) and non-dominant ($p < 0.006$) upper arms and pelvis ($p < 0.0003$). The differences between the characteristic jerk of rested and fatigued states were not significant for the both hands and forearms. Thus, the results show that the upper arm and pelvis are more suitable locations for placement of sensors to monitor fatigue as opposed to the hands and forearms.

The standard deviation of the characteristic jerk for both rested and fatigued states was found to drop as the body segments was located farther away from the hands. It was also found to be lower for the non-dominant than the dominant segment, except for the fatigued forearms. These results correlate well with the t-test results. They indicate that the spurious accelerations caused by impacts during mortar handling raise the noise floor of the hands acceleration signal, which is further amplified by numerical differentiation to obtain the jerk. The spurious accelerations diminish as the impact travels along body segments towards the trunk. Romero et al. [14] reported that impact forces diminish as they travel along the human body away from the point of impact due to dampening. The drop in spurious accelerations, in turn, reduces the noise floor of the jerk as the segment distance from the hands increase, reaching a minimum at the trunk. This is indicated by the elevated standard deviation of the hands jerk and the drop in the standard deviation as the segment distance from the hands increase to reach a minimum at the trunk. Similarly, as the noise floor drops, the change in jerk from rested state to fatigued state becomes more significant for the farther segments from the impacts, namely the upper arms and trunk. For this reason, care must be taken when selecting the locations of IMU for fatigue monitoring.

Another important finding is that the difference between the rested $J_r$ and fatigued $J_f$ characteristic jerk for the non-dominant upper arm was more significant than that of the dominant upper arm. are greater for the non-dominant than the dominant upper arm. This is possibly a result of a lower level of spurious accelerations due to impacts, and thus a lower noise floor, on the non-dominant side than the dominant side.

**Table 1. MEANS, STANDARD DEVIATIONS, *p*-VALUES OF THE CHARACTERISTIC JERK [g/s] IN RESTED AND FATIGUED STATES**

| Body Segment | | First 5 Lifts (g/s) | Last 5 Lifts (g/s) | *p* value |
|---|---|---|---|---|
| Hand | Dominant | 2.82 ± 1.17 | 2.98 ± 1.26 | 0.509 |
| | Non-dominant | 2.40 ± 0.88 | 2.63 ± 0.94 | 0.203 |
| Forearm | Dominant | 2.38 ± 0.81 | 2.58 ± 0.83 | 0.214 |
| | Non-dominant | 2.08 ± 0.80 | 2.40 ± 0.85 | 0.06 |
| Upper arm | Dominant | 1.67 ± 0.53 | 1.88 ± 0.47 | 0.043* |
| | Non-dominant | 1.59 ± 0.46 | 1.82 ± 0.37 | 0.006* |
| Pelvis | | 0.98 ± 0.24 | 1.19 ± 0.32 | 0.0003* |

The body segment data provided is the mean ± SD for all participants. *Significant difference ($p < 0.05$) between the rested and fatigued characteristic jerk.

## CONCLUSIONS

The current study tested the feasibility of using the jerk values obtained from wearable IMU sensors for the detection of physical fatigue. A repetitive bricklaying task was selected as a pilot study. The results from the study indicate that the jerk values derived from IMU sensors can be used to detect physical fatigue in a non-controlled environment. The experimental result demonstrated that the upper arms and pelvis are the optimal sensor locations to detect physical fatigue during bricklaying. On the other hand, the IMUs located at the hands and forearms do not show a significant difference in jerk value which is probably due to an elevated noise floor in the recorded acceleration due to repeated impact events during mortar handling.

We conclude that while jerk can detect fatigue, it is sensitive to the level of the noise floor in the underlying acceleration signal. Care should be taken to attach the accelerometer(s) in question to a body segment(s) active in the task at hand while being as far as possible from shocks and impacts. Using the acceleration of a non-dominant limb may also enhance jerk detection of fatigue.

Jerk appears to be a useful metric for developing warning systems against high levels of physical fatigue, designing better work schedules, and other methods to improve workers' health and safety. Furthermore, the proposed approach uses only one or a few wireless motion sensors, which allows for on-site detection of physical fatigue in a practical manner without technical sophistication. The low cost and simplicity of deploying the proposed method opens the doors for physical fatigue detection variety of work tasks. Further study will investigate the use of jerk in other labor-intensive trades (e.g. carpentry work).


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