Feasibility of Wearable Electromyography (EMG) to Assess Construction Workers' Muscle Fatigue

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Abstract

Due to the labor-intensive nature of construction tasks, a large number of construction workers frequently suffer from excessive muscle fatigue. Workers' muscle fatigue can adversely affect their productivity, safety, and well-being. Several attempts have been made to assess workers' fatigue using subjective methods (e.g., fatigue questionnaire). Despite, the success of subjective methods in assessing workers' fatigue in a long period, these methods have limited utility on construction sites. For instance, these methods interrupt workers' ongoing tasks. These methods are also subject to high biases. To address these issues, this study aims to examine the feasibility of a wearable Electromyography (EMG) sensor to measure the electrical impulses produced by workers' muscles as a means to continuously evaluate workers muscle fatigue without interfering with their ongoing tasks. EMG signals were acquired from eight subjects while lifting a concrete block using their upper limbs (i.e., elbow and shoulder muscles). As the first step, filtering methods (e.g., bandpass filter, rolling filter, and Hampel filter) were applied to reduce EMG signal artifacts. After removing signal artifacts, to examine the potential of EMG in measuring workers' muscle fatigue, various EMG signal metrics were calculated in time domain (e.g., Signal Mean Absolute Value (MAV) and Root Mean Square (RMS)) and frequency domain (e.g., Median Frequency (MDF) and Mean Frequency (MEF)). Subjects' perceived muscle exertion (Borg CR-10 scale) was used as a baseline to compare the muscle exertion identified by EMG signals. Results show a significant difference in EMG parameters while subjects were exerting different fatigue levels. Results confirm the feasibility of the wearable EMG to evaluate workers' muscle fatigue as means for assessing their physical stress on construction sites.

Keywords

Wearable electromyography (EMG) • Local muscle fatigue • Physical fatigue • Wearable biosensors • Workers' productivity • Safety • Health • Signal processing

22.1 Introduction

Construction is one of the most labor-intensive occupations in which workers are repetitively performing physically demanding tasks [1]. As a result, construction workers often suffer from a significant level of muscle fatigue that adversely affects their productivity, safety, and health [2]. Workers' fatigue has been introduced as one of the major factors that increase workers' error rate and lead to unsafe work actions [3]. Also, Workers' fatigue adversely affects their alertness, reaction time, mental acuity and disposition [4]. For these reasons, it is essential to mitigate the factors and tasks associated with workers' muscle exertion. The first step toward mitigating fatigue in the workplace is to evaluate muscle exertion. Evaluating the level of workers' muscle fatigue in planned tasks before engaging in these tasks can greatly contribute to

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identifying the tasks that may lead to muscle exertion. Then, adjusting the scheduled tasks and actions before severe fatigue takes place will enhance workers' safety, productivity, and well-being.

Previous research efforts have attempted to assess workers' muscle fatigue using subjective assessment (e.g., fatigue questionnaires) [5, 6]. However, interrupting workers' ongoing work to complete questionnaires interferes with time-sensitive tasks. Also, such methods are subjective and therefore include high biases. In addition to subjective assessment of physical fatigue, theoretical models of physiological or mechanical mechanisms (e.g., mathematical models) have been developed to assess workers' muscle fatigue [7, 8]. Despite their potential to evaluate workers' muscle fatigue, these mathematical models are limited in the context of construction tasks that have time-varying force exertions and irregular pauses and short breaks [8]. Therefore, there is a definite need for a measurable and noninvasive method that can continuously measure construction workers' muscle fatigue.

In recent decades, one well-known method for measuring human beings' muscle fatigue is the use of electromyography (EMG), which is the measurement of the electrical impulses produced by the muscle during its contraction [9]. The EMG signal has been used widely in the clinical domain for the diagnosis of muscle fatigue [10–12] and nerve disorders [13, 14]. However, the EMG signal acquired in the clinical domain is based on invasive methods, either by inserting a needle directly into the muscle through the skin or by measuring surface EMG using wired electrodes placed on the skin. Despite the high quality of the EMG signals recorded using these methods, the use of these methods to measure muscle activity is impractical at construction sites due to their invasive experimental settings. However, with recent advancement in sensing technologies, wearable and portable sensors are available and contributed to enhancing job site conditions [15–29]. In this regard, a wearable EMG can open a new door toward a noninvasive and continuous measurement of workers' muscle activity.

Despite the potential of a wearable EMG to collect workers' muscle activity while performing different tasks, the feasibility of a wearable EMG to measure workers' muscle fatigue has not been tested. To address this issue, this study tests the feasibility of a wearable Electromyography (EMG) sensor to measure the electrical impulses produced by workers' muscles as a means of continuously evaluating their muscle exertion and recovery without interfering with their ongoing tasks. To this end, the authors conducted an experiment to collect EMG signals of eight subjects' upper limb muscles (e.g., bicep and shoulder muscle) while they were experiencing different fatigue levels. The authors applied various filtering methods (e.g., a bandpass filter, a rolling filter, and a Hampel filter) to reduce EMG signal artifacts. Then the feasibility of a wearable EMG in distinguishing different levels of muscle fatigue was examined by comparing various metrics (e.g., signal Mean Absolute Value (MAV), Root Mean Square (RMS), Mean Frequency (MNF), and Median Frequency (MDF)) that were calculated based on the EMG signal. The Borg Rate of Perceived Exertion (RPE) scale, which is a well-known method to evaluate perceived muscle exertion, was used as a baseline to measure subjects' muscle fatigue level. Lastly, the feasibility of a wearable EMG sensor in measuring workers' muscle fatigue was examined by comparing the EMG-based metrics for different levels of muscle exertion.

22.2 Surface EMG to Measure Workers' Muscle Fatigue

Surface Electromyography (EMG) is a noninvasive method that provides useful information about the early manifestation of muscle fatigue by measuring the electrical activity of the muscle [9]. Even though raw EMG signals offers valuable information about the muscle activity, these signals need to be processed to measure muscle fatigue level. EMG signals are informative only if they can be quantified. Several studies have illustrated that there exists a significant relationship between EMG parameters (e.g., mean signal amplitude, root mean square, signal variance, mean power frequency, and median power frequency) and muscle fatigue [10–12, 30].

In this section, the authors explain two essential steps to examine the feasibility of measuring construction workers' muscle fatigue using a wearable EMG sensor. Before analyzing the signal, one essential step is to reduce signal noises and signal artifacts. After reducing signal artifacts, to examine the feasibility of a wearable EMG to distinguish different muscle fatigue levels, the authors' extracted different metrics based on the EMG signals.

22.2.1 Artifacts Removal

EMG signal quality can be adversely affected by different sources and forms of signal artifacts. The recorded EMG signal contains a component that shows the electrical response of the muscle activity (desired signal) as well as various noise components that come from sources other than muscle activity (undesired signals) [9]. Ambient noise, motion artifacts, electrical noise from power lines, and inherent instability of the EMG signal are main noise sources [31, 32]. The authors

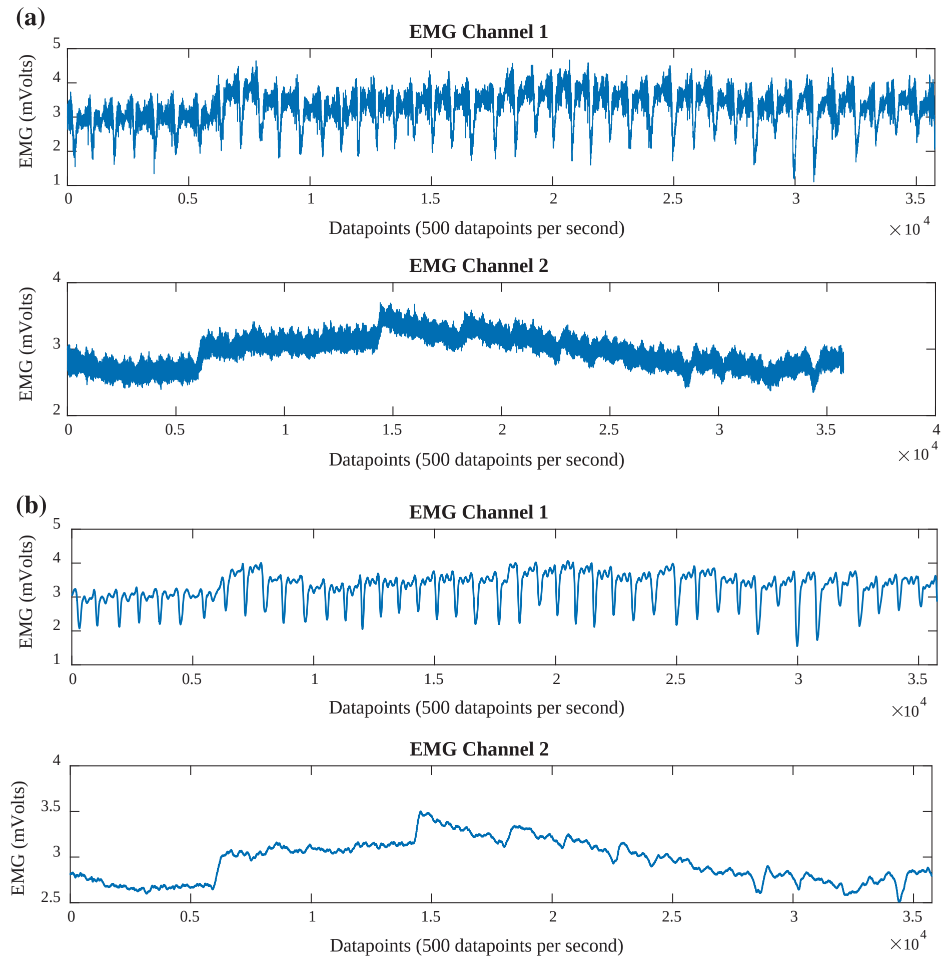

Fig. 22.1 EMG signal artifacts removal: **a** Raw EMG signals recorded from a worker's bicep muscle (Channel 1) and shoulder muscle (Channel 2); **b** Filtered EMG signals

applied different filtering methods (e.g., a bandpass filter, a rolling filter, a Hampel filter and a notch filter) to remove noises from the EMG signals. To remove ambient noise that comes from external electromagnetic sources (e.g., device wire noise), the authors applied a notch filter with a cutoff frequency of 60 Hz, which was recommended by previous researchers as an appropriate cutoff frequency to remove this type of noise [33]. To remove signal outliers a Hampel filter was applied, Hampel filter has been introduced as a useful method to remove EMG signal outliers [34]. A bandpass filter with the lower cutoff frequency of (0.5 Hz) and higher cutoff frequency of 250 Hz was applied to reduce other external signal artifacts (e.g., motion artifacts, ambient noise, and inherent instability of the EMG signals) [35]. To smooth the signal and to avoid aliasing in the data, a rolling filter was applied [31]. Figure 22.1 shows the raw EMG signals and the filtered EMG signals.

22.2.2 EMG-Based Metrics

Signal Mean Absolute Value (MAV), Root Mean Square (RMS), Mean Frequency (MEF), and Median Frequency (MDF) were calculated as the metrics to examine the potential of EMG in measuring workers' muscle fatigue. All of these metrics have been used widely in the clinical domain to assess muscle fatigue. EMG amplitude related parameters in the time domain (e.g., MAV and RMS) have been introduced as the informative metrics to evaluate muscle fatigue and estimate the endurance time [36, 37]. In addition, to the parameters that are calculated in the time domain, previous researchers found that changes in EMG signal patterns in frequency domain also are significantly associated with a decline in muscle force from the fresh state and therefore, it has a high potential to be used to measure muscle fatigue [12, 38]. Table 22.1 shows the extracted parameters based on EMG signal in time and frequency domains. In this research, the authors extracted different EMG signal

Table 22.1 Extracted EMG signal metrics in time and frequency domain

Domain	Parameters	Equation	Explanation
Time domain	Mean Absolute Value (MAV)	$MAV = \frac{\sum_{i=1}^{N} \lvert EMG_i \rvert}{N}$	Average absolute value of EMG amplitude
	Root Mean Square Level (RMS)	$RMS = \sqrt{\frac{\sum_{i=1}^{N} EMG^2}{N}}$	Norm 2 of the EMG amplitude divided by the square root of the number of samples
Frequency domain	Average Frequency (MEF)	$power(EMG, f \in [0Hz, 250Hz])$	Power of the EMG the signal in the frequency domain in the interval $[[0Hz, 250Hz]]$
	Median Frequency (MDF)	$power(EMG, f \in [0Hz, MDF]) = power(EMG, f \in [MDF, 250Hz])$	Half of the signal power is distributed in the frequencies less than MDF

parameters from a block of 500 consecutive data point (1 s) since A single EMG data point is not informative to Due to the high temporal resolution of EMG recording (500 data point in a second).

22.3 Experimental Setting

To examine the feasibility of the EMG-based parameters in measuring workers' muscle fatigue, the authors conducted an experiment and measured the electrical activity of eight healthy subjects while performing tasks with different fatigue level. Subjects were asked to use their upper limbs (i.e., elbow and shoulder muscles) and perform two tasks. In Task 1, subjects were asked to use their shoulder muscle (shoulder flexions from 0° to 120°) to lift a concrete brick that weighed 30% of their maximum shoulder muscle strength (Fig. 22.2a). In Task 2, subjects were asked to lift a concert brick that weighted 30% of their maximum bicep muscle strength using their bicep muscle (Fig. 22.2b). Subjects' maximum muscle strength of elbow and shoulder muscle was measured using a hand-held manual muscle tester (e.g., JTECH Commander Muscle Tester). Also, subjects were asked to maintain a constant lifting speed to prevent accelerations in lifting and to minimize variations in

Fig. 22.2 Experimental setup: **a** Task 1: lifting concert brick using shoulder muscle; **b** Task 2: lifting concrete block using bicep muscle; **c** Placement of EMG channels; **d** An off-the-shelf wearable EMG sensor that was used in this study; **e** Placement of EMG electrodes on muscle peak

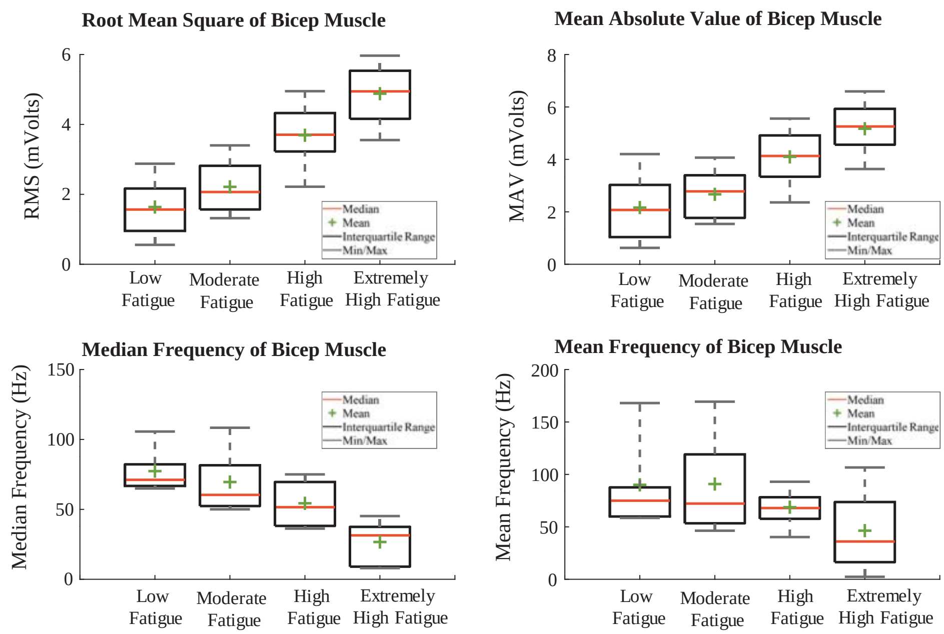

Fig. 22.3 The values of MAV, RMS, MEF, and MDF for bicep muscle

forces during different tasks. EMG signals were acquired from subjects' bicep and shoulder muscles across two channels using a wearable EMG device (Fig. 22.2c, d). EMG electrodes were placed parallel with the muscle fiber between the motor point and the tendinous insertion, near the center of the muscle. A reference electrode was placed far away from the bicep and shoulder muscles at an electrically neutral point of the body (Fig. 22.2e). The Borg Rate of Perceived Exertion scale [39], which assesses perceived exertion of the subjects was used as a baseline to assess subjects' perceived exertion [39]. Subjects were asked to rate their upper body muscles (shoulder muscle in Task 1 and bicep muscle in Task 2) fatigue level every 15 s. According to subjects' perceived exertion, the recorded EMG signals were divided into: Low Fatigue Level

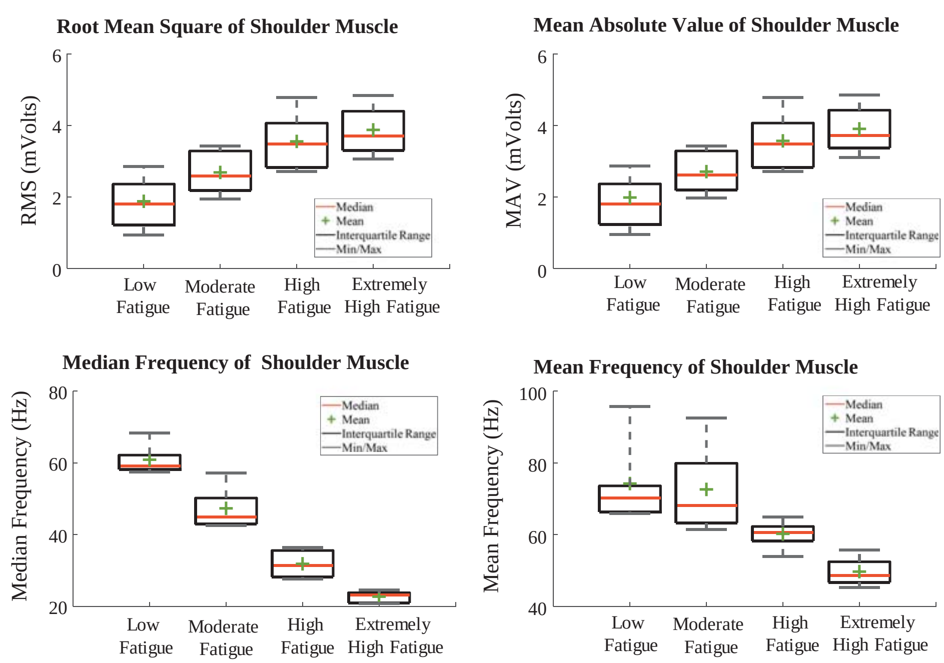

Fig. 22.4 The values of MAV, RMS, MEF, and MDF for shoulder muscle

(RPE scale between 0 and 2), Moderate Fatigue Level (RPE scale between 3 and 4), High Fatigue Level (RPE scale between 5 and 7), and Extremely High Fatigue Level (RPE scale between 8 and 10) [39].

22.4 Results and Findings

Figures 22.3 and 22.4 show the calculated EMG-based metrics values for bicep and shoulder muscles while subjects' were performed the experiment tasks under different fatigue levels. Results indicated a clear difference in MAB, RMS, MEF and MDF values while subjects were perceiving different fatigue levels for both bicep and shoulder muscles. Results show higher MAB, RMS values while subjects experienced higher muscle fatigue level (higher Borg scale rate) compared to the situation with less muscle fatigue (lower Borg scale rate). Higher MAB and RMS values show higher muscle exertion [40]. This confirms the feasibility of the extracted metrics in the time domain to measure workers' upper limb muscle fatigue.

In addition, there was a clear difference in the metrics that were calculated in the frequency domain (MEF and MDF) among different fatigue levels. The results of this study are in accordance with the previous studies in the clinical domains that stated a lower MEF and MDF values shows greater muscle fatigue level [41]. Furthermore, the values of MEF and MDF are consistent, and both illustrated that subjects' experience higher muscle fatigue while they keep lifting the concert bricks continuously. In comparison of time and frequency domain metrics, the metrics that were calculated in the frequency domain led to a higher performance in distinguishing different levels of fatigue; this can be related to less sensitivity of these metrics to the signal noise as well as data aliasing [42].

22.5 Conclusion

The present study was designed to determine the feasibility of a wearable EMG sensor to measure construction workers' upper limb muscle fatigue. The results of this study show the feasibility of the wearable EMG to evaluate workers' muscle fatigue, which can result in measuring physical stress at construction sites. The results showed that higher muscle fatigue level leads to higher MAB and RMS values and Lower MEF and MDF values. These finding may be used to improve construction workers' productivity, safety, and well-being by developing an automatic and mountainous framework to measure workers' muscle fatigue based on their EMG signal. It is recommended that further research be undertaken to validate the use of current metrics in this study in measuring construction workers' fatigue through additional experiments with a larger number of subjects on different muscle groups.

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