Fatigue Detection from EMG Signals: Feature-Based Analysis

Steven N. Wilson, *University of Ottawa*

***Abstract*—Detecting muscle fatigue accurately is critical in sport related fields, and rehabilitation. This project aims to investigate fatigue detection using electromyography (EMG) signals, comparing traditional feature-based methods. The three key EMG features used were Root Mean Square (RMS), Mean Absolute Value (MAV), and Median Frequency (MDF), which were extracted from EMG signals recorded during dynamic dumbbell curls using the MyoWare sensor. These features were analyzed to observe their trends over time and their ability to reveal a fatigue threshold.**

I. Background and Motivation

Muscle fatigue is a critical physiological phenomenon that occurs during intense physical activity, leading to a temporary decrease in the muscle's ability to generate force. Understanding muscle fatigue is essential for hypertrophy—the increase in muscle size that results from resistance training. Hypertrophy is stimulated through mechanical tension, muscle damage, and metabolic stress, all of which can be influenced by the level of muscle fatigue experienced during training sessions. As muscles become fatigued, they may recruit more motor units and fibers to maintain performance, which can enhance muscle growth when managed correctly. Nonetheless, excessive fatigue can lead to an increased risk of injury and prolonged recovery time, all of which hinder training progress. Effective monitoring and management of muscle fatigue is crucial for athletes and individuals that want to maximize their performance while minimizing the risk of injury.

Based on these considerations, there is a great opportunity to test different techniques for assessing muscle fatigue. This project evaluates using a combination of Root Mean Square (RMS), Mean Absolute Value (MAV), and Median Frequency (MDF) features. The MyoWare 2.0 EMG sensor, a low-cost portable sensor, was used to record EMG signals from the bicep muscle while performing dynamic dumbbell curls over a 45-second interval. This work demonstrates the potential for incorporating technologies into wearable devices to gain valuable insights for more effective and targeted training strategies that promote optimal hypertrophy, overall fitness and recovery.

II. Related Work

Previous research has explored the use of EMG for muscle fatigue assessment in various settings. Studies have shown that changes in EMG signal characteristics, such as root mean squared (RMS) amplitude and frequency spectrum shifts, can effectively indicate muscle fatigue. Recently, there has been a growing interest in applying machine learning techniques to EMG data to improve fatigue prediction and accuracy. It is becoming more common the use of learning algorithms to analyze EMG signals to identify patterns associated with muscle fatigue. However, most existing methods require laboratory settings or more complex setups.

III. Objective

The primary objective of this project is to evaluate and compare the effectiveness of traditional EMG features (RMS, MAV, MDF) for detecting muscle fatigue thresholds during dynamic exercise. More specifically, the project aims to assess the ability of these features to indicate muscle fatigue.

IV. Hardware and Methodology

A. Hardware Description

In order to use the EMG sensor the Arduino Uno was the microcontroller used for the data acquisition. The data transfer between the Arduino Uno and the host computer was done through serial communication via USB. The Arduino processes the analog output from the MyoWare sensor, converting it to digital values, and streams the data to the host computer.

The EMG signal was recorded with the MyoWare 2.0 EMG sensor which is very compact and non-invasive. The sensor captures muscle activation signals by measuring electrical potentials generated during muscle contractions. The sensor operates with an input voltage of 3.3V-5V, with an analog output of 0-5V and a bandwidth frequency response within 20-500 Hz. The design of the sensor allows easy electrode attachment and placement on the target muscle, in this case the bicep.

Stick-on electrodes were used for EMG signal acquisition, these electrodes provide a conductive interface between the skin and the MyoWare sensor. The adhesive backing allowed a secure attachment to the skin while performing dynamic movements.

The MyoWare 2.0 sensor was connected to the Arduino Uno via analog input pins, with 5V power supplied through the Arduino. The stick-on electrodes were directly attached to the EMG sensor. This hardware configuration allowed a portable and compact solution for recording EMG signals during dynamic muscle contractions.

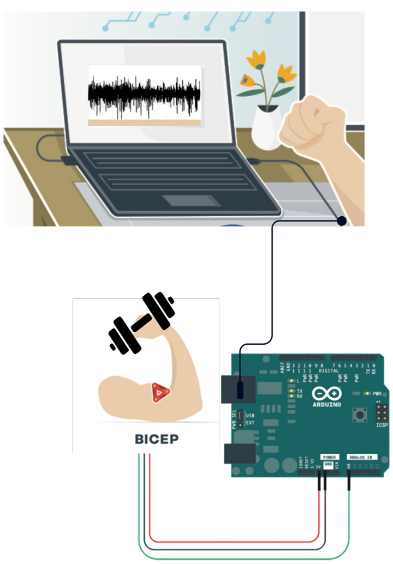

Figure I. EMG Sensor, Arduino Uno and Host Computer Configuration

B. *Data Collection*

The EMG signals are recorded using the MyoWare 2.0 EMG sensor to evaluate muscle fatigue during dynamic bicep curls. The biceps brachii muscle was targeted, and data was collected while the participant performed dynamic dumbbell curls. The sensor was attached following the standard electrode placement guidelines to optimize signal quality. The recorded signals included timestamps, raw EMG values, and were exported as CSV files for further analysis. A total of 10 samples were collected, consisting of 3 sessions lasting 30 seconds and 7 sessions lasting 45 seconds. The files for the 45-second sessions contained approximately 22,000 data points each, sampled at a frequency of 500 Hz.

The EMG sensor was connected to the Arduino Uno microcontroller, which digitize the analog EMG signal and transmitted it to a computer. The Arduino Ide was used to configure the microcontroller, and the baud rate was set to 115200 to ensure smooth serial communication. The terminal software CoolTerm was used to log and download the serial output.

C. *Preprocessing*

To ensure signal integrity and quality before feature extraction, three preprocessing steps were applied to the EMG data. These steps included baseline correction, filtering, and smoothing, all implemented using Python in Google Colab. These methods were validated using visualizations at each stage to confirm the preprocessing outputs aligned with expected signal behavior.

Baseline Correction was performed, the baseline was calculate as the mean of the raw signal values, which was the subtracted from each data point. The step ensured the signal oscillated around zero, removing low-frequency noise. Bandpass filtering was used to isolate the most useful frequency range of the EGM signal, focusing on the dominant power range of 20-150 Hz.

A 4th-order Butterworth bandpass filter was applied with cutoff frequencies of 20 Hz and 249 Hz. This was chosen to remove low frequency artifacts and high-frequency noise. To enhance signal clarity, a rolling average filter was applied with a window size of 50 samples. This smoothing technique helped to preserve signal trends while reducing noise spikes.

D. *Feature Extraction*

Feature extraction was performed to transform the preprocessed EMG signals into metrics that capture relevant information of muscle activity and fatigue. These features were selected based on established use in previous works for analysis of EGM signals for identifying changes in muscle fatigue activation and thresholds.

Time domain features represent the magnitudes and variations of the EMG signal, which are representative of motor unit recruitment of the target muscle during a contraction. Root Mean Square (RMS) represents the square root of the mean of the squared values in each segment and is usually used as a measure of the signal's overall strength. An increase in RMS is commonly associated with the recruitment of additional motor units as the muscle fatigues. The Mean Absolute Value (MAV) calculates the average of the absolute values of the EMG signal within a segment. The standard deviation of the signal amplitude was calculated to capture the variability of muscle activation.

Frequency domain features provide insight into the power distribution of the EMG signal, which allows us to identify shifts caused by muscle fatigue. Median Frequency (MDF) is the frequency at which the power spectrum is equally divided into two halves. Computed from the Power Spectral Density of the signal. The Welch method was used to estimate the PSD of each segment, the cumulative sum of the PSD was used to locate where 50% of the total power is reached.

To summarize the behaviour of each feature across all the samples the mean and standard deviation of each feature were calculated for all segments. This aggregation provided additional metrics to describe tendencies in the data.

V. Results and Discussion

The smoothed EMG signal captured during a dynamic dumbbell curl session exhibits the clear oscillations with varying amplitude that correspond to the muscle contraction and relaxation during the exercise. The EMG signal appears to be symmetric around zero, showing the effective baseline correction. The smoothing process has successfully reduced the transient noise spikes.

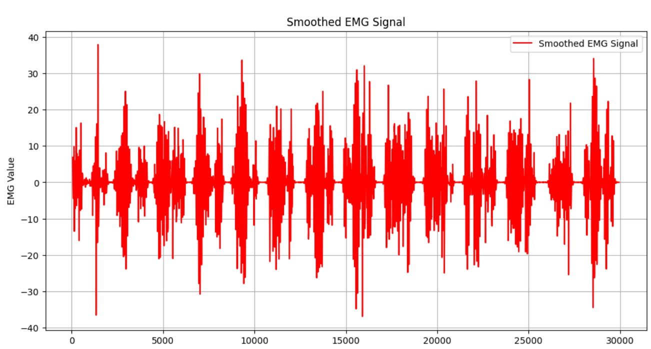

Figure II. Smoothed EMG Signal

Figure III. illustrates the trend of Median Frequency (MDF) overtime, the mean MDF values plotted in a solid line and the shaded region the ±1 standard deviation. We can observe that the MDF values remain relatively steady around 40-50 Hz during the first 15-20 seconds of the session. After 20 seconds, the MDF displays increased variability, with more fluctuations and peaks. The steady MDF values at the begging stage suggest that the muscle was operating efficiently with no significant fatigue. In the mid to final stages the increased variability may indicate the onset of early fatigue, however, the sharp spikes could be due to noise.

A gradual decline in MDF would have been a clear sign of muscle fatigue which is not present in these results.

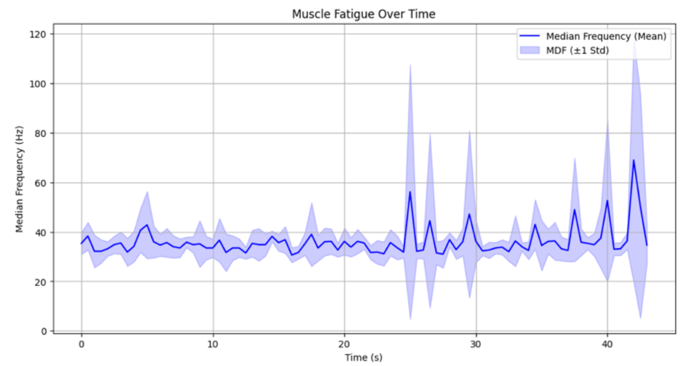

Figure III. Median Frequency

The trend of the Root Mean Square (RMS) value which is illustrated in Figure IV. shows a gradual increase over the duration of the exercise, indicating rising levels of muscle activation. RMS also shows the periodic oscillations corresponding to contraction and relaxation during the dumbbell curl exercise. RMS is a direct measure of the amplitude of the muscle activation, which aligns to the response of sustained effort, where greater activation is required to maintain output.

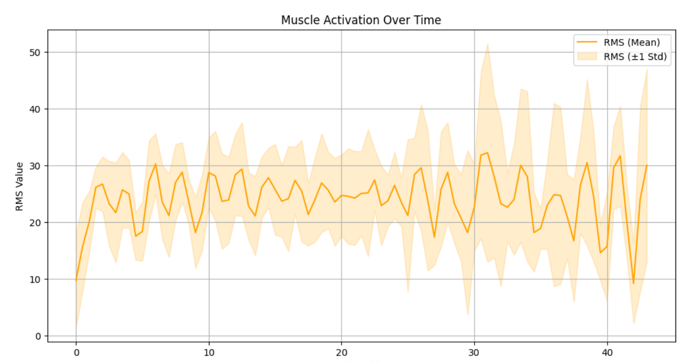

Figure IV. RMS Value

The Mean Absolute Value (MAV) presented in Figure V. also shows the periodic oscillation corresponding to the muscle contraction and oscillation. The shaded region broadens after 20 seconds, indicating increasing variability of the MAV values during the later stages of the session. The very slight upward trend aligns with the physiological expectations during fatigue. As muscle fiber fatigue, additional motor units are required, increasing the overall signal amplitude. MAV is a direct measure of muscle activation and is correlated to force production.

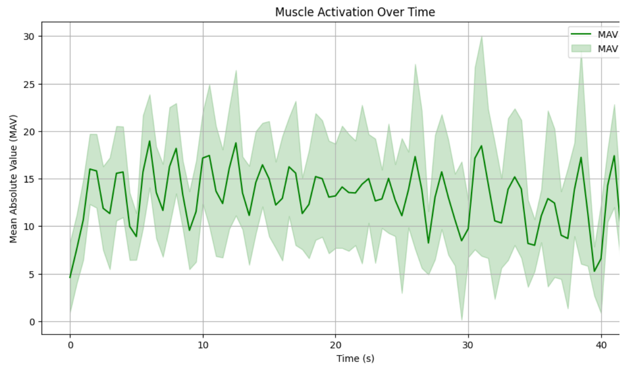

Figure V. MAV Value

The Figure VI. below depicts the trends of the three EMG features Median Frequency (MDF), Root Mean Square (RMS), and Mean Absolute Value (MAV). Each feature's mean values are plotted with corresponding thresholds marked as dashed lines.

The threshold for RMS and MAV captures the point at which muscle activation significantly increases, incorrectly indicating the onset of fatigue. This is marked response as the need for additional motor unit at the start is high. MDF provide a more realistic view by detecting the spectral shifts that align with fatigue progression.

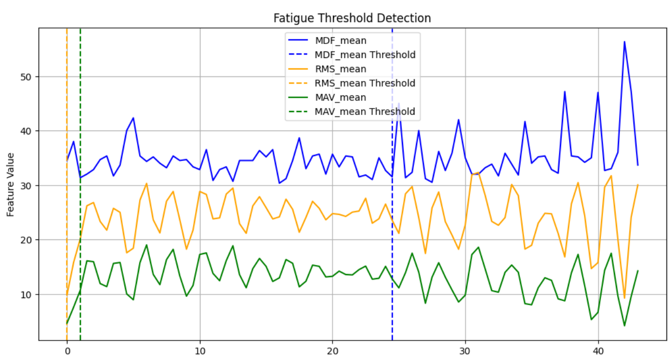

Figure VI. Fatigue Threshold Detection

The analysis of the EMG data through various features Median Frequency (MDF), Root Mean Square (RMS), and Mean Absolute Value (MAV) provide valuable insights into muscle activation and fatigue during dynamic dumbbell curls. Some of the key findings were that periodic oscillations in RMS and MAV effectively captures the contraction relaxation phases of the exercise and showed slight upward trends over time. MDF provided complimentary insights associated to fatigue but were much less pronounces. It was observed that there was a growing variability in all features at the later stages of the sessions, serving also as an indicator of fatigue.

For future work it would be useful to improve the challenges with signal variability, and equipment limitations. Even though these limitations were present the results demonstrate the potential of EMG feature analysis for fatigue monitoring, especially when implemented with high precision devices. This project offers insight into developing muscle fatigue detection devices that could be implemented in wearable systems.

VI. References

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VII. Annex

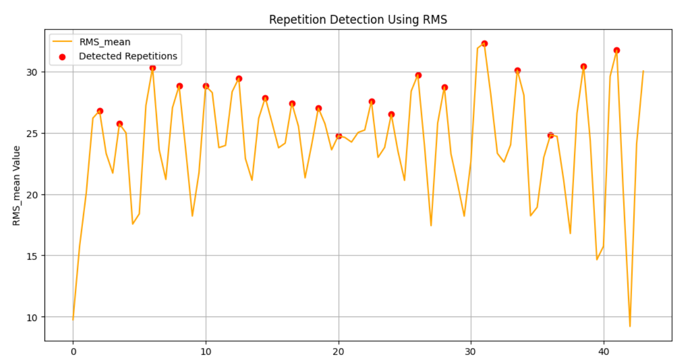

Figure I. Repetition Detection