Muscle Fatigue Detection and Classification for Weight Training Guidance and Exercise Prescription

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***Abstract*—*GymBuddy* is a mobile application that is used together with a Myo armband. It acts like a human gym trainer that recommends weight training routines for arms to achieve the user's fitness goal. When a trainer designs an exercise program, one main factor that would be taken into consideration is the fitness capacity of the client, which is the muscle strength and endurance for weight training, in order to maximise the effectiveness of the training without getting injured. This component report proposes a high-level design for a muscle fatigue detection module, which would detect the skeletal muscle fatigue level of the user's forearm in order to avoid injury and design workout routines.**

I. Introduction

Weight training is a kind of resistance training, which can increase muscle strength and muscle endurance, resulting in a gain in muscle size (muscle hypertrophy) [1]. When fitness experts are designing exercise routines, one common principal to use is F.I.T.T., which are frequency, intensity, time and type. All four factors would have to be tailored to individuals according to a person's age, sex, current fitness level and the available resources for training in order to maximise exercise effectiveness and avoid injuries [2] [3].

GymBuddy is a mobile application that acts as a personal gym trainer for weight training in arms, and is used in aid with a Myo armband, which contains 8 surface electromyographic (sEMG) sensors, a gyroscope, accelerometer and magnetometer. It is important for *GymBuddy* to be able to assess an individual's fitness ability to ensure the designed activities is at an optimal level, which means it is not too high that the person will injure, but not too low where the fitness goal will be under-achieved.

When a person is performing physical activities, skeletal muscles contract continuously and dynamically to produce force and movements. As a person exercises, the muscles will get tired at different rates, depending on the exercise intensity and duration. Therefore, measuring the muscle fatigue level of an individual would help *GymBuddy* to understand the health of the user's muscles.

This *Muscle Fatigue Detection and Prediction* module in *GymBuddy* would provide the *Real-time Feedback* module with the muscle fatiguing level, so it could warn the user when his muscles are fatiguing too quickly, and also allow the *Workout Routine Generation* module to design suitable exercise programs according to the user's fitness ability.

II. Related Work

A. Muscle Fatigue Detection

The contraction of skeletal muscles are controlled by electrical stimulation, which is known as action potential, and oxygen will be delivered to muscles to generate energy [4]. During intense exercise, the energy consumption could be quicker than the oxygen supply to muscles. Therefore, the inadequate supply of oxygen would lead to an anaerobic energy production in the working muscles, and the anaerobic respiration produces a by-product, which is lactic acid.

Therefore, one common method to determine skeletal muscle fatigue is to measure the lactate concentration of muscles using blood samples [5]. However, this method would not allow real-time tracking of the muscle fatiguing progress, and would give an overall fatigue level of an area instead of a particular muscle.

Therefore, researchers have been evaluating ways to determine local muscle fatigue by analysing sEMG. Using sEMG for muscle fatigue analysis is particularly useful as it is non-invasive, and also allows real-time tracking. The 8 medical grade EMG sensors on the Myo armband will allow *GymBuddy* to extract the raw EMG signal from the user's forearm by using the SDK released by Thalmic Labs [6], and therefore skeletal muscle fatigue analysis would be a good choice for this system.

The accumulation of lactic acid would slow down the propagation of action potentials along muscles [7], or namely Muscle Fibre Conduction Velocity (MFCV). MFCV could be calculated by dividing the distance between electrodes by the delay of EMG signals between the electrodes [8]. Also, spectrum of the EMG signal will be compressed as the MFCV decreases [9]. MFCV would give a detailed view on muscle fatigue and recovery [10]. However, it will be challenging to determine the MFCV using Myo as it would require the exact distance between two electrodes as well as the delay of EMG signal, and there would be many pairing combinations among the 8 electrodes in Myo.

Instead of using MFCV, many researches have conducted time-domain and frequency-domain signal processing techniques to analyse skeletal muscle fatigue.

1) Time Domain Analysis: The drop of MFCV will cause the signal amplitude of sEMG to increase [11], as there is a low-pass filtering effect in tissues [5]. Sörnmo and Laguna have also stated that "The amplitude of the surface EMG is a fundamental quantity which increases monotonically with the force developed in the muscle" [4]. In order to evaluate the sEMG amplitude, the mean absolute value (MAV) and root mean square (RMS) could be calculated to observe the changes in signal amplitude and signal power respectively. An increase in MAV and RMS should be observed as muscles fatigue. The two metrics are defined by the following equations:

$$MAV = \frac{\sum_n |A_n|}{N} \qquad RMS = \sqrt{\frac{\sum_n {A_n}^2}{N}}$$

where A_n is the n^{th} EMG amplitude measurement of N observations.

Cifrek et al. have suggested that the sEMG amplitude is seldom being used to determine muscle fatigue alone [5]. Usually the amplitude is used with other spectral analysis to indicate local muscle fatigue.

2) Frequency Domain Analysis: Although much information could be extracted from the amplitude characterisation of the sEMG in terms of MAV or RMS, another common approach is to conduct power spectral analysis [4]. During the muscle fatiguing process, the

MFCV slows down and compresses the power spectrum of the sEMG, leading to a shift of the spectrum towards the lower frequencies [5] [12] [4]. Therefore, it would be difficult to observe and quantify such slowing behaviour of the signal using time domain analysis [4]. There are many spectral parameters that could be used to analyse the spectral shape, and among all variables, the most popular metrics being used are the mean frequency (MNF) and median frequency (MDF) of the power spectrum [12] [13] [4]. As the spectral distribution shifts to the lower frequencies when muscle fatigues, the MNF and MDF of the spectrum will fall. The equations for MNF and MDF calculation are stated as below:

$$MNF = \frac{\int_0^{\pi} \omega S_x(e^{j\omega}) d\omega}{\int_0^{\pi} S_x(e^{j\omega}) d\omega} \qquad MDF = \frac{1}{2}\int_0^{\frac{\omega_s}{2}} S_x d\omega$$

where ω is frequency $(rads^{-1})$, ω_s is the sampling frequency, S_x is the power spectral density of the EMG signal.

When comparing MFCV to MNF, MNF recovers more quickly than MFCV [14] and have a less linear decrease than MFCV. Although MFCV would provide better insights in muscle condition, the frequency spectral analysis and amplitude analysis of the extracted sEMG signals from all 8 electrodes should be sufficient to deduce the muscle fatigue at a high level view, and would also suit the Myo armband more as aforementioned. The rate of decrease of MNF could act as an index to represent the level of fatigue.

The sEMG signals are dependent upon the fatigue state as well as the exerted muscle force. Therefore, Luttmann et al. have developed a joint analysis of EMG spectrum and amplitude (JASA) framework to categorise the EMG variations into fatigue, recovery, force increase or force decrease by taking both the amplitude and spectral changes into account [15] [16]. The four status are determined as below [16]:

- **Increase in Muscle Force:**
  Increase in both amplitude and MNF
- **Muscle Fatigue:**
  Increase in amplitude but decrease in MNF
- **Recovery from Fatigue:**
  Amplitude drops and MNF rises
- **Decrease in Muscle Force:**
  Decrease in both amplitude and MNF

This JASA method provides a simple and clean method to distinguish the four cases of muscle status.

B. Muscle Fatigue Classification

Al-Mulla et al. from University of Essex have attempted to differentiate sEMG activity of bicep muscle among three fatigue stages: Non-Fatigue, Transition-to-Fatigue and Fatigue [17]. Nine features were selected to classify the signals, which are instantaneous median frequency, median frequency (MDF), regression coefficients, higher order statistics, root mean square (RMS), wavelet, total band power, dominant frequency and RMS of selected band. A k-means clustering algorithm that was modified to a classifer algorithm (Supervised k-means) by Al-Harbi et al. [18] was implemented to distinguish the three classes. From their results, it was concluded that RMS and MDF gives the best class separation for fatigue recognition.

Al-Mulla et al. have also worked on another study to predict and detect localised muscle fatigue, and classify the EMG signal into two stages: Non-fatigue or Transition-to-Fatigue [19]. Two features, instantaneous median frequency and the total band power, was used in this study and Linear Discriminant Analysis (LDA) was used as the classification algorithm. A mean classification accuracy of 90% was achieved with an error of 4% [19].

III. Implementation and Current Progress

The objective of the *Muscle Fatigue Detection and Prediction* module is to track the health of muscles during the weight training, and also records how quickly a user's muscle would fatigue in order to provide the appropriate exercise prescription. The input of the module would be the raw EMG signals from the 8 sensor pods in the Myo armband, and the fatigue level would be passed to the *Real-time Feedback* module for warnings if it exceeds a certain threshold, and the rate of muscle fatiguing would be passed to the *Workout Routine Generation* module for workout routine generation.

At a high-level view, the module would extract raw EMG of the user's forearm using the SDK developed by Thalmic Labs [20]. Then features would be extracted from the EMG signal, and transmitted to the classification module which determines the muscle fatigue level using historic data. Lastly, the fatigue level and rate of fatiguing will be passed to the *Real-Time Feedback* and *Workout Routine Generation* modules respectively.

A. Raw EMG Extraction and Signal Pre-Processing

In April 2015, Thalmic Labs have updated the Myo iOS SDK (0.5.0) which allows developers to extract EMG signals from the 8 EMG sensors on the Myo armband [21]. EMG data will be recorded throughout the whole workout session, including rests in between fitness activities to ensure the continuous changes in EMG signals are captured.

Myo armband requires a gesture sync before use, then followed by a warming up period in order to recognise gestures. However, since gesture recognition is not needed for the purpose of *GymBuddy*, the gesture sync procedure is relatively less important. However, a warm-up period (typically within a minute) is still useful for the Myo armband to capture quality EMG signals, and therefore, users should wear the Myo armband at the beginning of the workout session to ensure quality signal is recorded.

Dr. Merletti have set the standards for EMG data reporting, and the standards are endorsed by the International Society of Electrophysiology and Kinesiology (ISEK) [22]. It was stated that "power density function of the surface EMG signals has negligible contributions outside the range 5-10 Hz to 400-450 Hz. The bandwidth of the amplifier-filter should be within this range e.g. high pass 5 Hz, low pass 500 Hz" [22]. This standard have been followed by many sEMG analysis and suggested by many books [23] [4].

According to the Nyquist theorem, the sampling frequency should be at least twice the highest cut-off frequency of the filter (i.e. 500 Hz), which means the sampling frequency of the EMG signal required for such band-pass filter would be at least 1000 Hz to avoid aliasing and ensure accuracy. However, when reviewing the EMG sensors in the Myo armband, each sensor only has a sampling rate of 200 Hz [6]. Therefore, such pre-processing standard is not applicable to the EMG signals extracted from the Myo armband. According the Myo Developers forum, pre-processing is already applied to the EMG signal before extraction, which takes away noises such as powerline interference. Therefore, the EMG data extracted should be good to process directly when being extracted using the SDK.

B. Features Extraction

From the reviewed studies, amplitude and frequency are the most popular measures being used to measure skeletal muscle fatigue. In order to evaluate whether these metrics are suitable to be used with the sEMG signals extracted from the Myo armband, a test was conducted with 3 test subjects aged between 21 to 22 on both arms. The test subjects were first asked to keep his arm relaxed and rest on a surface for 30 seconds, and the status is named as *Static*. Next, the test subjects were instructed to perform forearm curls with 1kg and 3kg dumbbells in 30 seconds intervals respectively. sEMG data was recorded throughout each session, and test subject is asked to rate their perceived exertion using the Borg Scale, which is a common scale used by sport coaches to assess the fatigue experienced by a person during resistance training [13]. The mean absolute value (MAV) and root mean square (RMS) of signal amplitude, and mean and median frequency of power spectrum were computed per second. The distribution of the data points are plotted and a best fit line is drawn to observe the change of metrics over time, with an example of test subject 1 shown in Fig 1. The slopes of each electrode and parameter is then compared, and results for of test subject 1 is displayed in Fig 2.

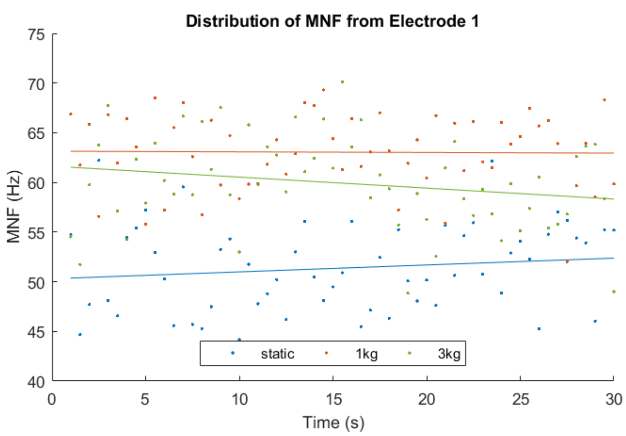

Fig. 1: Example of MNF Distribution and Regression with Different Loads from Electrode 1 for Test Subject 1

According to many studies, amplitude (MAV and RMS) should increase and frequency (MNF and MDF) should decrease as muscle fatigues. From Fig 2, MAV and MDF has the best performance, where 4 out of 8 electrodes follows the suggested trend (MAV: electrode 4, 5, 6, 7; MDF: 1, 3, 4, 8). Electrodes 1, 4 and 8 also gives a decreasing MNF as the load increases. If static mode is not included, more electrodes would have agreed with the expected trends. It is possible that the EMG at static state would behave differently as the hand gesture is different from the forearm curl motion, where the test subject is asked to grab a dumbbell, which could have caused a difference in the EMG spectrum.

When looking at the change of frequency over time in particular, electrode 5 behaves differently as compared to other electrodes, where it gives an increasing MNF and MDF with increasing exercise intensity. As the Myo armband surrounds the circumference of the forearm, it tracks all muscles on it. It is possible that some particular muscles are being used more than other muscles when performing the forearm curls. Also, as suggested earlier in the JASA framework, an increase in MNF could be due to an increase in muscle force, which would happen when a person is exerting force in order to carry the dumbbell as well. Therefore, another potential reason of the abnormal behaviour is that particular muscle tracked by electrode 5 has a stronger muscle strength and endurance as compared to other muscles, so the particular muscle was exerting force but not being fatigued with the load.

Therefore, MAV, MDF and MNF should be good features to be used for classifying the fatigue level using sEMG. However, there are a few other physical factors that should be taken into consideration when estimating a person's muscle strength, such as sex, age, height and weight. Also, the motion being performed (such as forearm curls or bicep curls) would affect the fatigue of forearm muscles differently. When doing bicep or tricep exercises, the upper arm muscles will fatigue more quickly. But since the individual will still need to hold the dumbbell while working out, fatigue should still be seen in forearm muscles, but at a much lower rate or level. Therefore, the kind of fitness activity that the user is performing should be another feature to be selected in the classification.

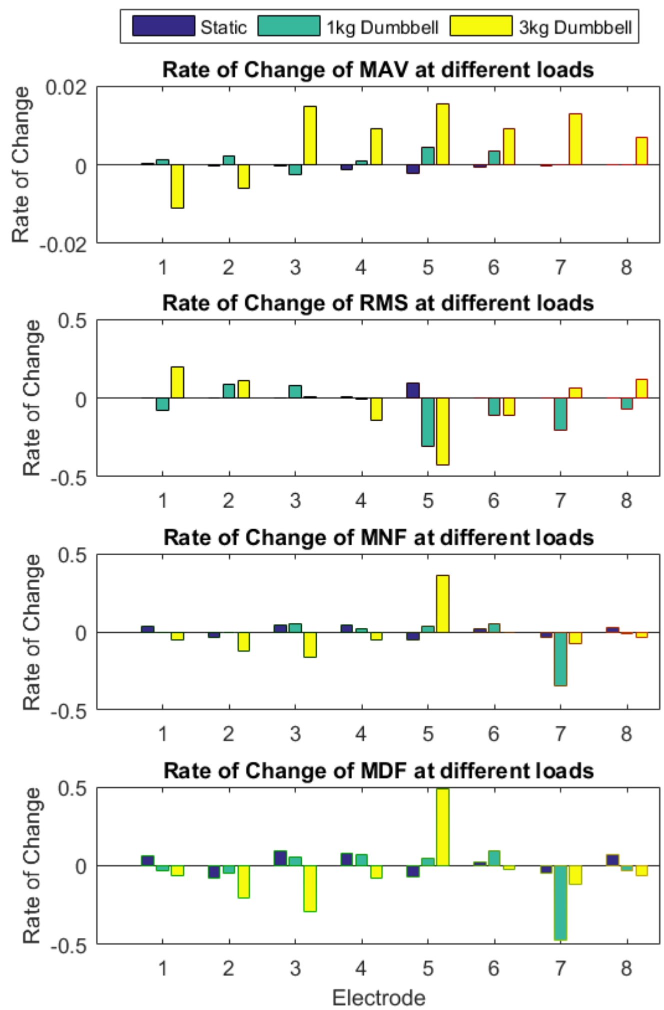

Fig. 2: Rate of Change of Parameters of Test Subject 1

C. Feature Selection and Classification Algorithm

To summarise, the 12 selected features are MAV, RMS, MNF, MDF, Age, Sex, Height, Weight, Dumbbell Weight, Dominant or Non-Dominant Arm, Fitness Activity and User ID. The Borg Scale rating will be the response class. Data collected from the 3 test subjects are fed into the classification learner in MATLAB. Among the available algorithms, a few of them give a 100% accuracy, which are Linear Support Vector Machines (SVM), Quadratic SVM, Cubic SVM, Medium Tree, Complex Tree and Bagged Trees. The confusion matrix of the training set using the Bagged Trees is shown in Fig 3.

Although many algorithms have given a perfect accuracy in the classification, there is only two fitness activities in the current data set. More data on other weight training activities, such as bicep curls and tricep curls, have to be collected before deciding the final classification algorithm to be picked. The next steps would be to capture more data for model training, including having more test subjects, a higher variety of dumbbell weights and fitness activities.

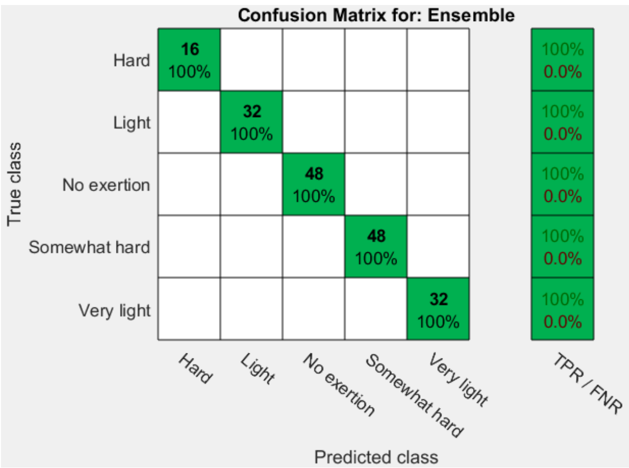

Fig. 3: Confusion Matrix Using Ensemble Classifier

D. Other Findings

During the collection of test data, it was found that the Myo armband went out-of-sync for 2 of the test subjects when forearm curls are performed with 3kg dumbbells. This could be because the main purpose of Myo is to detect hand gestures through sEMG pattern recognition. When an individual is holding 3kg of weight, the sEMG signal will become relatively abnormal as compared to the normal hand gestures when no load is carried, which causes Myo to determine the armband might have gone out-of-sync. Yet when evaluating the affected set of EMG data, the recorded signal does not seem to behave differently. So it is believed that the Myo armband is just losing the ability to recognise hand gestures at that point, but does not affect the EMG extraction. However, when the armband is out-of-sync, it provides a haptic feedback to the user, where test subjects have expressed such vibration is very disturbing during the exercise. More investigation have to be done to confirm carrying a heavy weight does not affect the EMG measurement, as well as whether the gesture sync could be forced-turned off when developing the iOS app.

IV. Conclusion

The muscle fatigue detection module serves as an important part of the *GymBuddy* system as it monitors the health of the user's muscle in real-time to avoid injury, and provides information to design an appropriate exercise routine to maximise workout effectiveness. In this report, different techniques to evaluate skeletal muscle fatigue is reviewed, and a high level system design is outlined.

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