EMG BASED SHORT-TERM AND LONG-TERM ANALYSIS OF MUSCLE FATIGUE DERIVED FROM AN ENDURANCE BASED EXERCISE REGIMEN

by

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ABSTRACT

The human muscular system is complex and multi-functional. Injuries to muscles or their neuromuscular controllers can result in impairment of various functions of the body, especially locomotion. Recovery from these injuries can be a very long and inconsistent process. A major cause of this is muscle fatigue. It has a significant detrimental effect on daily functional activities that require repetitive motion, postural control, or manipulation of objects. Currently, there are no objective methods to indicate how fatigue changes with exercise. The ability to detect the onset of fatigue is therefore crucial in developing a quantitative metric to identify muscle performance and its changes over a specified period of time.

This study consists of the development of a wearable EMG data acquisition device which will in turn facilitate in quantification and detection of muscle fatigue during an endurance based exercise routine. Data acquisition involves the usage of standard conventional wet electrodes and custom made dry electrodes. Data are acquired from test subjects’ biceps to identify short-term and long-term changes in muscle fatigue and the subsequent resistance to it, as well as its effects on endurance based therapeutic exercise interventions. Acquisition and analysis of long term and short term data can also provide meaningful insights in determining the optimal endurance exercise regimen for neuromuscular rehabilitation, sports rehabilitation and also for people following any kind of exercise regimen for general fitness.
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CHAPTER 1
INTRODUCTION

The human muscular system is complex and multi-functional. Injuries to the muscles or their neuromuscular controllers can result in impairment of various functions of the body, especially locomotion. Muscle injuries often result from repetitive injuries, trauma associated with sports, poor body mechanics, musculoskeletal disorders, neuromuscular disorders like stroke, and other accidents. Recovery from these injuries can be a very long process.

Stroke is caused by either ischemia or by sudden hemorrhage. It is also the leading cause of serious long-term disability and causes a reduction in mobility in more than half of stroke survivors age 65 and above[1]. Muscle fatigue is a major manifestation of muscle injury and stroke. If on any contractile activity, the force or power generated by a muscle decrease, then it will result in the muscle getting fatigued[2]. Ultimately, this leads to decreased activity times, decreased mobility, and prolonged clinical rehabilitation times. Muscle fatigue can be affected by factors resulting from metabolism and fatigue reactants during contractile activity such as inorganic phosphate, hydrogen ions, reactive oxygen species, lactate, heat shock protein and orosomucoid [3]. Therefore, it has a significant detrimental effect on daily activities like motion that requires strong muscles and also on athletic performance.

Post stroke, patients are subjected to prescribed exercises for improvement in balance, fitness, coordination, etc. This is often done in conjunction with walking or standing and is known as task specific activity. Currently, there are no methods to indicate how fatigue changes with exercise especially in a home based setting. The ability to detect the onset of
fatigue is therefore crucial in developing a quantitative metric to identify muscle performance and its changes over a specified period of time.

This study consists of the development of a wearable EMG data acquisition device which will in turn facilitate quantification and detection of muscle fatigue during an endurance based exercise regimen. The study comprises of amplitude analysis of EMG signal using linear envelope. The data acquisition involves the usage of standard conventional wet electrodes and custom made dry electrodes. Data are acquired from test subjects’ biceps to identify long-term changes in muscle fatigue and the subsequent resistance to it, as well as its effects on endurance based therapeutic exercise interventions.
CHAPTER 2

BACKGROUND

MUSCLES

Muscle tissues perform many functions like movement, maintenance and change of body posture, heat production, protection of internal organs, contraction of heart to pump blood, etc. Muscle cells, or myocytes, originate from the mesodermal layer during embryonic development and form excitable and contractile tissue. Muscles are predominantly bifurcated into three functional groups, namely: skeletal muscles, smooth muscles and cardiac muscles.

1. Smooth muscles - They are short, spindle shaped and have no striations on them. These are predominantly associated with the walls of internal organs and are responsible for involuntary functions such as peristalsis, respiration, involuntary movements, etc.

2. Skeletal muscles – They are long, cylindrical and have striations present on them. They are attached to the bones via tendons and also to body orifices. Skeletal muscles are responsible for movement, joint stabilization, protection of organs, heat production and maintenance of body posture. Bicep brachii, the muscle group targeted in this study falls under this group.

3. Cardiac muscles - These cells are typically branched, short and striated and form the walls of the heart. Cardio myocytes contract and pumps blood through the body.
Since this study is based on human movement, it is important to understand the basis of classification of skeletal muscles. The primary metabolic pathway that a muscle fibre utilizes to generate energy, determines if a fibre is glycolytic or oxidative. If a muscle fibre produces ATP anaerobically, then, such a fibre is classified as glycolytic and oxidative otherwise [4]. Based on this, muscle fibres can be further classified into three groups: -

1. Slow oxidative fibres/Slow twitch muscles – These make up to 50% of skeletal muscles and are small, dark-red fibres that produces ATP aerobically[5]. These are capable of long contractions and does not fatigue easily.

2. Fast-oxidative glycolytic muscle fibres /Fast twitch resistant– Fast oxidative muscle fibres are medium, dark-red fibres and primarily produce ATP aerobically [5]. As the glycogen content in them is high, they also have the capability to produce ATP anaerobically. These muscle fibres contract and relax faster than slow twitch muscles.

3. Fast-glycolytic fibres/Fast-twitch fatigable – Fast-glycolytic muscle fibres produce fast and powerful contractions but in turn gets fatigued easily. They are characterized as large white fibres that produces adenosine triphosphate anaerobically [5].

Additionally, the size principle of motor neuron recruitment determines how motor units are recruited size-wise from smallest to the largest[6]. Hence, motor recruitments occur in the order of:

Slow twitch → Fast twitch resistant → Fast twitch fatigable
ANATOMY OF SKELETAL MUSCLES

CONNECTIVE TISSUE OF THE MUSCLE

The hypodermis and fascia separate muscles from skin. The hypodermis is a subcutaneous fat layer that lies beneath both epidermis and dermis. The fascia is a protective and supportive layer to the muscles and is composed of dense bundles of connective tissue fibres. They also serve as the entry and exit pathways for blood vessels, neurons and the lymphatic system.

Fascia gives rise to three additional supportive connective tissues namely epimysium, perimysium and endomysium. The epimysium is the outermost protective layer that encloses the muscle. The perimysium is the intermediate layer that wraps muscle fibre bundles known as fascicles, while, the endomysium is the layer of connective tissue that is found wrapped around every individual muscle cell[5].

Figure 2.1 Anatomy and connective tissues of a skeletal muscle. Adapted from [4]
CELLULAR COMPONENTS OF A MUSCLE FIBRE

The plasma membrane of a muscle fibre is known as the sarcolemma. Sarcolemma plays a crucial role in the muscle contractile mechanism as it is electrically excitable in nature. Myofibrils are cylindrical structures that are found inside the muscle fibre, making up the muscle contractile units. They are composed of thick filaments, myosin, thin filaments, actin, as well as troponin, tropomyosin[5]. These proteins facilitate the activation of a muscle and subsequent muscle contractions. For example, these proteins prevent myosin from binding to actin when the muscle is in a relaxed state. When actin and myosin bind they allow the muscle fibres to shorten. Alternating arrangements of actin and myosin, results in the formation of sarcomeres which are the basic contractile units of skeletal muscles [7].

Multiple mitochondria supports these structures and produces vast amounts of ATP to enable the energy intensive contractile function[7].

On its surface, sarcolemma has openings that lead to a network of transverse tubules. They release calcium from the sarcoplasmic reticulum and are filled with extracellular fluid [8]. The calcium ions facilitate the depolarization of the muscle cell which in turn activates muscle contraction, and consequently the activation of the sarcomeres which produce tension within the muscles.
SARCOMERES AND SLIDING FILAMENT THEORY

Sarcomeres are the functional units of a muscle. M line is at the centre of a sarcomere to which myosin myofilaments bind. The length between two Z-lines is termed as sarcomere. Actin filaments are anchored to the Z-line and myosin filaments are anchored to the M-line. I band surround the Z-line and is composed of actin filaments. A band extends to the entire length of the myosin filament. A bands extend from myosin and have H zone at its centre within which is the M-line. The striated appearance of the skeletal muscle is due to this alternating I and A bands[5]

During contraction, I band and H zone disappear or shorten[10]. The length of A band remains constant during contraction[11-13]. A bands of different sarcomeres move closer during contraction.
Actin and myosin slide over one another, resulting in the shortening of the sarcomere. During relaxation, tension is released and results in the expansion of I band and H zone.

Muscle growth occurs by hypertrophy of muscle fibres by addition of myofibrils for increase in muscle mass or by addition of new sarcomeres to the extremities of a muscle fibre for increase in length[14]

CROSS-BRIDGE FORMATION

The cross-bridges are the active components in contraction. When myosin head attaches to actin myofilament, it results in the formation cross bridges. Calcium ions bind to troponin units on actin filaments. This results in the displacement of tropomyosin which exposes myosin binding sites. Myosin head has to be activated before the cross bridge formation. This happens by the hydrolysis of adenosine triphosphate (ATP) into adenosine diphosphate (ADP) and inorganic phosphate. Myosin releases inorganic phosphate and binds to the actin filament resulting in the cross-bridge formation.

The myosin heads then pull the actin towards the centre of the sarcomere resulting in the gliding motion between the two filaments using the energy produced from ATP hydrolysis. This is termed as power stroke and at this point ADP is released. The cross bridge detaches when ATP binds to myosin again. Reactivation of myosin occurs when ATP is again hydrolysed to ADP and inorganic phosphate.
Figure 2.3 Cross-bridge muscle contraction cycle. Adapted from [15]
EXCITATION- CONTRACTION COUPLING

MOTOR NEURONS AND STRUCTURE

Motor neurons are typically multipolar as they have multiple dendrites and a single axon. Motor neurons are found in the central nervous system and have their axons outside the central nervous system to control muscles.

A myoneural junction is the interface between a muscle cell and its controlling motor neuron. It is here that the neural impulses are transmitted to a muscle.

The motor-end plates and nerve-end plates do not have a direct contact but are separated by a small space known as the synaptic cleft. The neuron releases acetylcholine (ACh) into the synaptic cleft, which binds to the receptors in the motor end place.

As a result, sarcolemma is depolarized and the action potential spreads across the sarcolemma and down the transverse tubules into the interior of the cell to the triads[16]. This results in the release of calcium and subsequent contractile muscle activity.
ACTION POTENTIAL CONDUCTION

The action potential is a sharp change of voltage across cell membrane of approximately +100mV [18]. Sodium, potassium and chloride ions are unequally distributed between the inside and outside of a cell which results in voltage change. During the state of rest, the concentration of sodium ions is higher outside than the inside the cell whereas a contrary situation exists for potassium ions. A neuronal membrane has a resting potential of -70 mV.
A chemical gradient is created when ionic separation occurs at the cell. The difference in charge distribution between the outside and the inside results in membrane potential.

Most ions cross the membrane by passive diffusion through an ion channel along their concentration gradient. These ion channels open as the cell membrane depolarizes, which leads to propagation of the signal along the length of the cell. The movement of the ions across the cell membrane results in the deviation of membrane potential from its resting potential.

During graded potential, the neuron quickly returns to its resting potential which is enabled by a sodium-potassium pump that uses energy generated by ATP hydrolysis to actively transport ions across membrane against their concentration gradient.
Action potential is triggered at the axon hillock and travels down an axon when the outside stimulation is large enough to bring the membrane potential from -70 mV to +30 mV (100 mV difference).

Once the cell membrane reaches the threshold voltage, sodium channels open and sodium ions move into cell. As more positive sodium ions enter the cell, the membrane potential approaches to 0 mV and eventually reaches +30mV. This is termed as depolarization.

As the membrane potential becomes positive, the sodium channel inactivation gate shuts and makes the channel inactivated. The change in membrane potential opens voltage-gated potassium channels. As a result, potassium ions flow out of the cell and results in repolarization.
As the potassium channels are slow to close, the membrane enter into a brief period of hyperpolarization. At this point, the potential is lower than the resting potential. The sodium-potassium pumps then re-establish the electrochemical gradients and resting potential.
A motor neuron along with its innervated muscle fibres is referred to as a motor unit. The frequency of the action potential controls the activity of the motor unit. A muscle fibre can only be innervated by a single motor neuron while a motor neuron can innervate more than one muscle fibre[4].

Figure 2.7 A single motor unit. Adapted from [20]
When the action potential of every individual fibre in the motor unit is superimposed, it results in a motor unit action potential[21].

![Figure 2.8 Representation of motor unit action potential. Adapted from [21]](image)

**ELECTROMYOGRAPHY (EMG)**

EMGs measure the electrical activity of the muscles. These electrical activities are usually generated when a muscle contracts, and it presents general neuromuscular activity. The EMG signal depends on the physiology and anatomy of the muscles and are controlled by the nervous system. Based on the positioning of the sensors which record EMGs, the properties and signal profiles can be significantly different. Most surface EMGs acquire information from multiple motor units at the same time resulting in the interaction between multiple signals[22]. This can lead to mixed efficacies of some EMG based studies, but nonetheless it is an important tool used to examine neuromuscular activity.
EMG signals are generally recorded within the 0-500 Hz frequency range, while the dominant energy range is between 50-150 Hz. Also, the peak to peak amplitude range is around 0-10 mV [23]. Since, the amplitude range is very small, EMG signals often require amplification during data processing and analysis. EMG signals are usually described in terms of frequency, phase and amplitude and is a time-based function[22]. Signal distortion and signal to noise ratio are two key concerns that affect the reproducibility of the signal[23]. It is important to note that EMG signals are greatly affected by motion artifacts which arises as a result of relative motion between tissues and the sensor itself.

Herein, EMGs will be used to identify the level of fatigue in a muscle. Changes in amplitude[24, 25] may be a possible indicator of muscle fatigue as described in earlier studies.

An example of a pre-processed EMG signal is shown in Fig. 2.9 -

![Figure 2.9 Pre-processed EMG signal](image-url)
Cifrek et al. in their study have mentioned about the use of surface electromyography as a method for monitoring muscle fatigue[26]. A study conducted as early as 1923 shows that the amplitude of individual action currents increase and the frequency of action currents tends to decrease when EMG of a rapidly fatigued muscle is assessed[27]. Adam et al. in their study have mentioned that the recruitment of additional motor units accompanied an increase in firing rate[28].

Viitasalo et al. in their EMG based study of rectus femoris muscle have reported that they analysed integrated EMG and observed increase in amplitude of the EMG signal. They observed the power density curve shift to the lower frequency and also observed that with respect to fatigue, the mean power frequency decreased linearly with time[24]. Hence, EMG signal amplitude as an indicator for fatigue is majorly used in conjugation with other analysis like EMG spectral analysis[26].

There has been a previous study that shows how a time constant dependent on the slope of the EMG average power (with respect to time) can define the rate of change of fatigue in muscles[29]. Mean and median frequency analysis is considered as a gold standard for fatigue detection in muscles using EMG[30].

This study focuses on EMG based amplitude time analysis, mean power analysis (time domain analysis) to assess long term and short term effects of fatigue. The study will also present a new design of dry electrode and the feature obtained from it to analyse muscle fatigue.
**EMG Electrodes**

EMG electrodes are attached to the body to measure muscle activity. The most common electrodes are intramuscular electrodes and surface electrodes. Surface electrodes are attached to the surface of the skin and are non-invasive. Intramuscular electrodes are attached surgically and record muscle activities from the muscle directly and hence are invasive.

**Non-Invasive EMG Electrodes**

The most common types of non-invasive EMG sensors are either gel based or dry electrodes. The most common type of electrodes sought after for recording the electrical activity of the muscles are conventional silver-silver chloride electrodes.

The wet (gel) electrodes usually have conductive adhesive electrolytic gel at the surface of contact between the skin and the electrode to increase conductivity.

Even though conventional wet electrodes provide high quality signals and are suitable for short term or clinical use, they are not recommended for long term use. This is because the gel eventually dries out which causes skin irritation and also results in subsequent signal degradation [31]. This can be addressed partially by the use of dry electrodes.
Dry electrodes consist of a metal, polymer or semiconductor with a thin dielectric surface layer next to the skin, and uses no electrolytic gel at the interface boundary layer. However, these electrodes are associated with higher noise levels during acquisition, often leading to more significant motion artifacts.

![Figure 2.10 Gel electrode](image)

**Invasive EMG Electrodes**

Invasive electrodes provide good signal specificity, precision and can be employed to record electrical activities of muscles deeper within the body. These electrodes are directly attached to the muscles. Signals obtained using these can provide single motor unit action potential/activity due to good selectivity[32].

Invasive electrode has surgical dependencies but at the same time are considered more accurate as they are directly attached to the muscle of interest. These electrodes are typically of two types, namely: Needle electrodes and Wire electrodes.
Single fibre EMG needle electrodes are used when the recording area is small, and can determine and discern individual muscle potentials. Wire electrodes are fine and are implanted into the muscles of interest and are less painful than needle electrodes[33].

Figure 2.11 a. Wire electrode  b. Needle electrode Adapted from [33]
ANATOMY OF BICEPS BRACHII

The biceps brachii is of utmost relevance in this study as this is the targeted muscle for the experiments described in more detail below.

The bicep brachii has a short head and a long head on its proximal attachment (see Fig. 2.12). The short head is attached to the tip of coracoid of scapula and the long head is attached to the supraglenoid tubercle of scapula. It is distally attached to the tuberosity of radius and fascia of forearm via bicipital aponeurosis. The biceps supinates the forearm and hence flexes the forearm[34].

Figure 2.12 Anatomy of bicep
CHAPTER 3
HYPOTHESIS

Muscle fatigue is a major manifestation of neuromuscular disorders like stroke and trauma, and can also be inflicted through athletic activities. It has a significant detrimental effect on daily functional activities that require repetitive motion, postural control, or manipulation of objects. Currently, there are no objective methods to indicate how fatigue changes with exercise. The ability to detect the onset of fatigue is therefore crucial in developing a quantitative metric to identify muscle performance and its changes over a specified period of time.

As described above in the background, it was shown that EMGs demonstrate time-based changes and power output based changes with the onset of fatigue. For example, EMG amplitude increases with fatigue due to the recruitment of additional motor units[24, 28]. This amplitude change can also be attributed to a higher synchronized motor unit recruitment which can be seen in paretic muscles with fatigue [35]. Based on these findings, it is expected that the slope of EMG power can indicate the rate at which the muscle may be fatiguing, as well as how fatigue changes over a long-term period. For example, an increasing amplitude in EMG power (dB per second) may represent a measure to identify how quickly the muscle is fatiguing during exercise. While a decrease of EMG power rates over a long-term (dB per day) may indicate how the muscle becomes more fatigue resistant over time.
The central hypothesis here is that the power slope derived from this study can be used to derive a performance metric to quantify muscle fatigue. This study will also demonstrate the rates of fatigue onset, and fatigue resistance (both short-term and long-term), and their rate of change based on the exercise. It will be of interest to examine how this trend varies between subjects with both dry and electrodes. It will also serve as a measure to assess the effectiveness and reproducibility of a new dry electrode design with respective to conventional wet electrodes.
CHAPTER 4

DEVICE

The device consists of a microcontroller, three rechargeable 9V batteries, Bluetooth shield and an EMG sensor. Both the microcontroller and the EMG sensor have built in features for signal pre-processing. The microcontroller used in this study is powered externally by a 9V rechargeable battery and powers up the Bluetooth shield. The EMG sensor is powered externally by two 9V batteries.

Figure 4.1 Device built for EMG acquisition
1. Micro controller

The microcontroller used in this design is an Arduino Pro Mini with ATmega328. It has a 16MHz bootloader with 5V regulator. The whole board weighs less than 2 grams and is 18x33x0.88 mm in dimension, making it an excellent choice for incorporation into a wearable device. It has 6 analog pins and 14 digital input/output pins. It uses 10-bit analog – digital converter (ADC) which implies that the 0-5 V are mapped from 0-1023. This component does not have a USB on board and utilizes external FTDI drivers for communication. This microcontroller can be powered externally by a 9 V battery or through a USB connected to a computer. The ATmega328 provides UART TTL serial communication, which is available on digital pins 0 (RX) and 1 (TX). Bluetooth shield used in this study is connected to these digital pins for seamless data transmission.

![Arduino Pro Mini](image)

**Figure 4.2 Arduino Pro mini**

The Arduino Pro Mini is powered externally in this study using a 9V rechargeable battery through the RAW and GND pins.
2. Bluetooth shield

Bluetooth shield used in this study is Bluefruit EZ-Link Breakout board. It is a serial link device. It supports baud rates 2400, 4800, 9600, 19200, 38400, 57600, 115200 and 230400.

![Figure 4.3 Bluefruit EZ-Link Breakout Board](image)

However, in this study the choice of baud rate is 9600 bits per second which translates to a transmission rate of 9600 bits of data in one second between the Bluetooth module and the laptop. The board also has a 6 pin FTDI-like header.

The Bluetooth module is powered by Arduino Pro Mini through its Vcc pin and supplies 5V. It has an on-board regulator that can take 3-16 supply voltage and convert it to 3V to power the RF module.

3. EMG sensor

A three lead differential muscle sensor called Muscle sensor v3 (Advancer Technologies, LLC) is used in this design (Figure 4.4). The sensor is powered externally by two 9V rechargeable batteries through its +Vs, -Vs and GND pins. The EMG sensor is connected to the microcontroller through SIG and GND pins. The output obtained is an amplified, rectified, and smoothed signal and requires no further pre-processing through signal processing software.
A set of 3 cables with connected snaps work at the interface of the electrode and the cable port of the electrode. Since, this electrode is a three lead system the RED cable’s snap is connected to the electrode that is placed in the middle of biceps muscle body and the blue cable’s snap is connected to the electrode that is positioned at one end of the muscle body. The black cable’s snap is attached to the electrode which is placed on the elbow for a bony reference.

![Muscle sensor v3](image)

The only disadvantage of the sensor was the double power supply requirement. It requires +Vs and –Vs which would need an additional power supply, making the unit more cumbersome.

RN 42, HC-05 Bluetooth modules and MyoWare muscle sensor were considered for incorporation to the device design initially. However, due to power consumption issue and other compatibility issues, these components were not used in this design.
ELECTRODE DESIGN AND SELECTION

For this study, conventional wet electrodes and dry electrodes are used for data acquisition.

1. Wet electrodes – Commercially available standard silver-silver chloride is used (Primary Care by MDP).

2. Dry electrodes - Compression sleeve electrode design and Ag-nylon textile electrode

   a. Compression sleeve electrode - Three pieces of a conductive plated fabric (SHIELDIT Super, LessEMF, USA) are stitched onto a compression sleeve with two attachments on the bicep area (W 5/8” x L 1 3/4”) and one attachment on the elbow to act as a reference (W 5/8” x L 2”).

   b. Ag-nylon textile dry electrode - This design utilizes a silver (Ag) plated (76%) nylon elastic fibre (24%) fabric (Stretch Conductive Fabric, LessEMF, USA). This fabric is attached to a deconstructed Ag-AgCl/wet electrode. The fabric is attached to the electrode with a conductive adhesive and is cut to match the size of a metal snap. An adhesive is used for the attachment of fabric to the metal snap, but does not interact with the skin/electrode interface[36].


Below are the plots obtained of the EMG signal obtained from each of the above mentioned designs:

![Figure 4.5 a. Ag-nylon textile dry electrode  b. Compression sleeve electrode](image_url)

![Figure 4.6 EMG signal acquired using compression sleeve electrode](image_url)
Figure 4.7 EMG signal acquired using Ag-nylon electrode
CHAPTER 5

METHODS

DATA ACQUISITION

The Muscle Sensor v3 acquires EMG data using electrodes positioned at the centre and end of bicep muscle as well as at the elbow (reference). These data are then sent to the analog input pins of Pro Mini. The Pro Mini has a 10-bit analog to digital converter which returns integer values from 0 to 1023. The microcontroller converts these analog values from a recorded voltage of 0-5V. Since, the design is intended to be a prototype for a wearable device, it was natural to choose a Bluetooth module to transmit data wirelessly to a laptop. The Bluetooth module used in this study works up to a range of ~10m distance. The software used to read the incoming data from the Bluetooth module is CoolTerm. CoolTerm is a serial port terminal software which exchanges text and other data between connected serial ports.

Figure 5.1 Block diagram representation of data acquisition
SUBJECT RECRUITMENT

This study was approved by the Institutional Review Board (IRB), University at Buffalo. Even though it is mentioned that 18 subjects will be recruited for the study in the IRB, the recruitment was restricted to 14 subjects out of which 8 subjects were mandated to stick to the hypertrophy exercise routine and 6 subjects for the endurance exercise routine. For this study a total of 6 healthy subjects were recruited. All the subjects were female and were within the age group of 24-26 years. Out of the 6 recruited subjects, 3 of them were fitted with wet electrodes, and the other 3 subjects were fitted with dry electrodes. Informed consent was obtained from all the participants and the data obtained from them was de-identified of any personal information.

Subject recruitment was done based on certain inclusion and exclusion criteria as follows:

Inclusion criteria:

- The subjects must be within the age group 18-30 years
- Subjects must have BMI in the range of 18.5 - 24.9[37].
- Subject must be healthy to lift low to moderate weights

Exclusion criteria:

- Subjects who have reservations against lifting weight within a comfortable limit of their own threshold.
• Subjects who are undergoing or have previously undergone treatment for cardiovascular, muscular, or other health concerns

• Subjects who refuse to provide informed consent.

• Individuals participating in active fitness programs or follow an exercise regimen at a gym, including weightlifting.

• Pregnant women

EXERCISE ROUTINE

For this study, a bicep curl exercise using a 5 lb dumbbell was chosen to isolate biceps muscle activity for endurance based exercise. Every participant was required to perform 20±2 repetitions of 5 sets per exercise schedule, twice a week (every Wednesday and Friday). The exercise roughly translates to extension and contraction of the arms as controlled by the bicep muscle. The exercise routine involved the use of a metronome which was set at 40 bpm (0.67 Hz) to achieve a standardized repetition rate. Each set lasted for about 1 minute and 50
seconds. They were then allowed take a break for about 1 minute, and continue on to their next set. This data was obtained for a period of 4 months.

DATA ANALYSIS

DATA PRE-PROCESSING

EMG signal acquired is already rectified, smoothed and amplified by the hardware on board the Muscle Sensor v3. The signal acquired was transmitted via Bluetooth module to the laptop. This signal was further pre–processed to remove zero values and NaN values in MATLAB. Code was written to accomplish this and can be found in the Appendix A section of this report.

The collected EMG signals were analysed in the time-domain for this study.

Time Domain Analysis

1. Amplitude slope analysis

It is of interest to measure how EMG amplitudes change with contraction over time. Therefore, the maximum amplitude peaks in volts (representing the highest amplitude value of each contraction) was plotted against time in seconds for each set. This plot represents how amplitude changes with respect to time within the same set and different sets of endurance based exercise. Using the basic fitting toolbox in MATLAB, a linear fit was generated for the data points.
A linear regression was fit based on the peak EMGs:

\[ y = mx + c \]  

(Eq.5.1)

Where ‘m’ is the slope of the line and ‘c’ is the y-intercept.

Figure 5.3 Representation of linear fit for maximum amplitude peaks

A steeper slope represents the larger effort put in by the muscle (volts per second) to lift the weight during exercise.

2. Mean power analysis

Mean power analysis provides a relationship to represent how muscle contraction power changes with respect to time as the muscle fatigues. The power of a signal is computed using Eq. 5.2. The power obtained is plotted with respect to time. Using the basic fitting toolbox in MATLAB, a linear fit was generated for the data points. The slope generated by the software can be either positive or negative based on with the signal value with respect to the reference signal. Usually, within sets on a same day, power is expected to increase and is represented
by a positive slope. This increase in power represents the rate of muscle fatigue as described earlier.

Power in decibels is given by the equations:

\[
\text{Power (dB)} = 20 \log_{10} \left( \frac{\text{Signal Voltage}}{\text{Reference Voltage}} \right) \quad \text{in terms of voltage} \quad \text{(Eq. 5.2)}
\]

\[
\text{Power (dB)} = 10 \log_{10} \left( \frac{\text{Signal Power}}{\text{Reference Power}} \right) \quad \text{in terms of power} \quad \text{(Eq. 5.3)}
\]

The reference voltage is computed as the mean of the signal acquired when the target muscle was at the state of rest; i.e., it is the average of the signal when the muscle does not experience any contractile force. The reference signal is also considered the noise floor for this study. The reference calculation is done for each data set every day with respect to the noise floor (reference). This is done in order to account for changes in sensor positioning, difference in muscle anatomy and physiology from subject to subject.

Figure 5.4 Reference voltage representation
CHAPTER 6
RESULTS

AMPLITUDE –TIME ANALYSIS

Figure 6.1 a. Amplitude versus time plot

Figure 6.1.a represents the EMG data that were obtained from subject 1. This signal is directly obtained from the Muscle Sensor v3 after pre-processing (amplification, rectification and smoothening). This image shows how the amplitude increases (2.86 V) with respect to time within a single set. The mean value of EMG signal increases by 120.74%
Figure 6.1.b represents the peak amplitudes corresponding to maximum muscle contraction within a single exercise set. This figure provides an easy representation of the peaks for better visualization. The linear fit (red line), here, provides information about the slope which is 0.12782 V/s. During this exercise, the EMG voltage output increased from approximately 1.85V to 4.71V (254.59%) output. A steeper slope represents the larger effort put in by the muscle (volts per second) to lift the weight during exercise. These data are representative for “good data” regarding muscle activity during exercise and are described further in tables 6.1 and 6.2 (the two tables below)
Table 6.1 Data collected using wet electrodes

Table 6.1 provides information about the data collected using wet electrodes. Total data sets refer to the total number of sets collected using wet electrodes. Good data sets provide with the number of datasets deemed usable. Bad data (refer Appendix C) sets indicate the number of data sets that were not considered for this study. The data in these sets are either corrupted with noise or has undergone baseline shift due to faulty placement of electrodes, lack of proper adhesion, etc. Useable data refers to the ratio of good data sets to total data sets and is represented in percentage. Data with positive slope (of the linear fit across maximum amplitude peaks) refers to the ratio of data sets with a positive slope to the entire data set and is again expressed as percentage. Table 6.1 provides information on amplitude-time data collected from wet electrodes. For subject 1, it can be seen that the useable data is 76.47% of which 78.46% data had a positive slope (of the linear fit across maximum amplitude peaks). Subject 2 provided with 85.71% of useable data of which 61.66% had a positive slope. Subject 3 has 84.61% of useable data of which 86.66% had positive slope.

<table>
<thead>
<tr>
<th>SUBJECT NO</th>
<th>TOTAL DATASETS</th>
<th>GOOD DATASETS</th>
<th>BAD DATASETS</th>
<th>USEABLE DATA IN PERCENTAGE</th>
<th>DATA WITH POSITIVE SLOPE FOR PEAK AMPLITUDE OUT OF USEABLE DATASETA IN PERCENTAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>85</td>
<td>65</td>
<td>20</td>
<td>76.47%</td>
<td>78.46%</td>
</tr>
<tr>
<td>2</td>
<td>70</td>
<td>60</td>
<td>10</td>
<td>85.71%</td>
<td>61.66%</td>
</tr>
<tr>
<td>3</td>
<td>65</td>
<td>55</td>
<td>10</td>
<td>84.61%</td>
<td>86.66%</td>
</tr>
</tbody>
</table>
### DATA COLLECTED USING DRY ELECTRODES

<table>
<thead>
<tr>
<th>SUBJECT NO</th>
<th>TOTAL DATASETS</th>
<th>GOOD DATASETS</th>
<th>BAD DATASETS</th>
<th>USEABLE DATA IN PERCENTAGE</th>
<th>DATA WITH POSITIVE SLOPE FOR PEAK AMPLITUDE OUT OF USEABLE DATASETA IN PERCENTAGE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>74</td>
<td>41</td>
<td>33</td>
<td>55.40%</td>
<td>92.68%</td>
</tr>
<tr>
<td>2</td>
<td>55</td>
<td>36</td>
<td>19</td>
<td>65.45%</td>
<td>75%</td>
</tr>
<tr>
<td>3</td>
<td>44</td>
<td>32</td>
<td>12</td>
<td>72.72%</td>
<td>75%</td>
</tr>
</tbody>
</table>

Table 6.2 Data collected using dry electrodes

Table 6.2 provides information about the data collected using dry electrodes. Total data sets refer to the total number of sets collected using dry electrodes. Good data sets provide with the number of datasets deemed usable. Bad data sets indicate the number of data sets that were not considered for this study. The data in these sets are either corrupted with noise or has undergone baseline shift due to faulty placement of electrodes, lack of proper adhesion, etc. Useable data refers to the ratio of good data sets to total data sets and is represented in percentage. Data with positive slope (of the linear fit across maximum amplitude peaks) refers to the ratio of data sets with a positive slope to the entire data set and is again expressed as percentage. Notable result here is that, for subject 1, it can be seen that the useable data is 55.4% of which 92.68% data had a positive slope (of the linear fit across maximum amplitude peaks). Subject 2 provided 65.45% of useable data of which 75% had a positive slope. Subject 3 had 72.72% of useable data of which 75% had positive slope.
Fig. 6.2.a This figure shows a plot of average power in dB versus days for subject 1. Subject 1 showed a decrease in average EMG power of 11.84 dB over a 100-day period as shown in Table 6.4. The magenta dots represent the average power of all the sets on that particular day and the green line represents the linear fit of these data. It is important to note the negative slope of the linear fit which is -0.16353 dB/day.
Fig. 6.2.b This figure shows a plot of average power in dB versus days for subject 2. Subject 2 shows a decrease in average EMG power of 14.23 dB over a 100-day period as shown in Table 6.4. The blue dots represent the average power of all the sets on that particular day and the red line represents the linear fit of these data. It is important to note the negative slope of the linear fit which is -0.15205 dB/day.
Fig. 6.2.c shows a plot of average power in dB versus days for subject 3. Subject 3 shows a decrease in average EMG power of 14.22 dB over a 91-day period as shown in Table 6.4. The green dots represent the average power of all the sets on that particular day and the pink line represents the linear fit of these data. It is important to note the negative slope of the linear fit which is -0.145205 dB/day.

<table>
<thead>
<tr>
<th>SUBJECT NUMBER</th>
<th>SLOPE (dB/day)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.16353</td>
</tr>
<tr>
<td>2</td>
<td>-0.15205</td>
</tr>
<tr>
<td>3</td>
<td>-0.145205</td>
</tr>
</tbody>
</table>

Table 6.3 Long term slope of the linear fit of average power for subjects 1,2,3

Table 6.3 compares the long term slope differences of the linear fit of average power for subjects 1,2,3. Notably, all data demonstrate a similar downward trend. The average slope across all 3 subjects was -0.153595 dB/day, with a standard deviation of 0.0092

<table>
<thead>
<tr>
<th></th>
<th>SUBJECT 1</th>
<th>SUBJECT 2</th>
<th>SUBJECT 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>POWER (dB)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DECEMBER</td>
<td>23.55</td>
<td>23.14</td>
<td>26.05</td>
</tr>
<tr>
<td>JANUARY</td>
<td>24.17</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>FEBRUARY</td>
<td>11.96</td>
<td>13.66</td>
<td>16.76</td>
</tr>
<tr>
<td>MARCH</td>
<td>11.71</td>
<td>8.91</td>
<td>11.83</td>
</tr>
</tbody>
</table>

Table 6.4 Average power month-wise in dB of subjects 1,2,3
Table 6.4 indicates the month-wise average power in dB for subjects 1, 2, 3. Subjects 2 and 3 were not able to continue testing in the lab during the month of January but continued the exercise routine in another setting. Thus, data are not available for January.

![Graph](image)

**Figure 6.3 Subject 1 – Long term plot – Dry electrode design**

Fig. 6.3 shows a plot of average power in dB versus days for subject 1 (dry electrode design). Subject 1 shows a decrease in average EMG power of 6.23 dB over a 64-day period. The purple dots represent the average power of all the sets on that particular day and the green line represents the linear fit of these data. It is important to note the negative slope of the linear fit which is -0.12778 dB/day.
Fig. 6.4 shows a plot of average power in dB versus set numbers for subject 2. Subject 2 shows an increase in EMG power of 6.11 dB over the 5 sets performed on the same day. The black dots represent the average power of each set on that particular day and the red line represents the linear fit of these data. It is important to note the positive slope of the linear fit which is 1.275 dB/sec.
CHAPTER 7
DISCUSSION

This study presents the design of a wearable device to demonstrate the long term and short term effects on muscle fatigue when an endurance based exercise is done for a period of time.

It is evident from figure 6.1.a and 6.1.b that the EMG amplitude increases with respect to time during a single exercise. This observation has been confirmed in the literature[24, 25], and coincides with expectations that EMG amplitude increases with muscle fatigue due to the recruitment of additional motor units. This recruitment is necessary to maintain tension required by the muscle when subjected to exercises. Thus, EMG amplitude increases with respect to time as the muscle fatigues as more motor units are recruited to support the tension/weight. Since these are the results that are expected, this information was used to determine which data were “good” and “bad” as listed in Table 6.1 and 6.2. Only these “good” data were then used in the remaining analyses. Notably, in Fig 6.1.a, the mean value of EMG signal increases by 120.74% and in Fig. 6.1.b the maximum voltage peak increased by 254.59%.

Table 6.1 provides information on amplitude-time data collected from wet electrodes. Subject 2 provided the most useable data while subject 1 provided the least. Subject 3 provided the data with the most positive slope (of the linear fit across maximum amplitude peaks) while subject 2, the least.
Table 6.2 provides information on amplitude-time data collected from dry electrodes. Here the subject 3 provided the most usable data while subject 1 provided the least. However, subject 1 provided the data with the most positive slopes while the other subjects were at par. In terms of usable data obtained from wet and dry electrodes, even though there is the observation that wet electrodes provided more usable data, it can be noted that the performance of dry electrode in terms of usability is comparable.

Fig. 6.2 a, b, and c indicates the long term power plot of subjects 1, 2 and 3 respectively. It is worthwhile to observe here that the slope of the linear fit of average power is negative for all the 3 subjects. As an individual performed exercise over the 4-month period, the maximum EMG peaks (voltage) and average power decreased. This means that the muscles did not recruit motor units at the same rate, and likely, it means that it did not fatigue as quickly. In other words, the slope indicates how the muscle becomes more fatigue resistant over time. Subject 1 started the 1st day of the study with 27.05 dB/sec and the power value decreased to 9.967 dB/sec towards the last day, while subject 2 started the 1st day of study with 26.03 dB/sec and ended with 12.3 dB/sec. For the subject 3, the power value decreased from 23.87 dB/sec to 10.72 dB/sec. This trend observed across the subjects are consistent with the hypothesis made in Chapter 3. As shown in Table 6.3, the slope value of subject 1 is -0.16353 dB/day, subject 2 is -0.15205 dB/day and subject 3 is -0.145205 dB/day. Since the slope of subject 1 is the steepest, it is hypothesized that the subject achieved slightly higher anti-fatiguing properties over time than the other subjects. Table 6.4 gives a month-wise perspective of the average power data. In fact, we see the same trend for all test subjects which further reinforces the result.
The same results can be seen for subjects using the dry electrodes. For example, Fig. 6.3 shows the long term average power plot for subject 1 over a period of 64 days. There is a noticeable decreasing trend in average power over a period of time with a slope of -0.12778 dB/day. Generally, the measurements using dry electrodes exhibit more motion artifacts which limits usable data but still, the same trend is observed.

Fig 6.4 shows a representation of short term average power per set (for all 5 sets) on the same day. Subject 2 showed an increase in EMG power of 6.11 dB over the 5 sets performed on the same day with a positive slope of 0.1275 dB/sec. Here, we notice an increasing trend in power indicating muscle fatigue within a day. This translates and is in concurrence with the hypothesis as the power required by the muscle to lift the weight over the short term or as within the same day here is more.

While the long term power trend can serve as an important muscle performance metric for rehabilitation and to quantify athletic performance over a period of time. This long term and short term data can also provide meaningful insights in determining the optimal endurance exercise regimen for rehabilitation, sports rehabilitation or other applications.

Based on this study, some modifications for future studies can be proposed. For example, though the dry electrode design here provides superior results than the compression sleeve electrode, the usability of the data is not as ideal as wet electrodes. This majorly arise from the electrode design. Since, the design here involves a deconstructed wet electrode design,
major issues such as adhesion of the electrode to skin and reusability exist. This results in excessive motion artifacts and can hamper with the signal quality. The future scope of work might be to incorporate better methods and design to tackle this issue of motion artifacts by improving this electrode design.

As described in the hypothesis, the increase in amplitude can be due to reasons like recruitment of additional motor units and motor unit synchronization. One of the future directions can be to delineate these findings to understand precisely about the amplitude change by using invasive wire EMG electrodes for muscle activity recording to gather information from a single motor unit.

It will be also interesting to see short term and long term effects of other exercise routines like strength based and hypertrophy based on muscle fatigue. This can help the therapist to decide what exercise routine works the best for what type of rehabilitation or therapeutic intervention. Multiple subject recruitment based on broader age and gender categories can be useful to derive meaningful solutions.
APPENDIX A

1. Arduino code for data acquisition

```c
void setup ()
{
  // initialize serial communication at 9600 bits per second:
  Serial.begin(9600);
}

// the loop routine runs over and over again forever:
void loop () {
  // read the input on analog pin 0:
  int sensorValue = analogRead(A0);

  // Convert the analog reading (which goes from 0 - 1023) to a voltage (0 - 5V):
  float voltage = sensorValue * (5.0 / 1023.0);

  // print out the value you read:
  Serial.println(voltage);
}
```

2. Code to find average power

```c
a(a==0) = []; // a is the data set
a (isnan (a)) = [];
ref= mean (a (1:10)); //1:10 denotes the position of the reference chosen
Power = 20*log 10 (a/ref);
```
APPENDIX B

Though this study basically focuses on time-domain analysis, it is also important to know the fundamentals of frequency domain analysis. This section explains the same.

Frequency Domain Analysis

1. Power spectral density

The Fourier transform of the autocorrelation function of an EMG signal is used to convert the signal from the time domain to the frequency domain. This provides the power spectral density[30]. The power spectral density provides a measure of signal power across the frequencies in which it is distributed within the signal.

Parseval’s identity conveys power of a time varying signal and is given by:

\[
\text{Power} = \frac{1}{N} \sum_{k=1}^{N-1} |x_k|^2 \quad \text{(Eq. B.1)}
\]

\(x_k\) – Fourier transform of the signal and \(N\) - Number of samples.

2. Mean and median frequencies

It has been noted that the frequency spectrum of an EMG signal presents itself with a downward shift when muscle fatigue sets in and hence, median and mean frequencies are
considered as standards for fatigue analysis when surface EMG is employed among techniques like wavelet analysis, RMS, zero crossing rate, etc.[30].

Power spectrum is divided into two parts of equal amplitude at a frequency termed as median frequency[30, 38, 39]. The concept of mean frequency is that, here, the summation of the product of frequency and power spectrum is obtained. This is then divided by the sum of power spectrum. This average frequency so computed is termed as mean frequency[30, 38, 39].

Median and mean frequency is given by[30]:-

**Median frequency (MDF)**

\[
\text{Median frequency (MDF)} = \sum_{j=1}^{M^{DF}} p(j) = \sum_{j=M^{DF}}^{M} p(j) = \frac{1}{2} \sum_{j=1}^{M} p(j) \tag{Eq. B.2}
\]

**Mean frequency (MNF)**

\[
\text{Mean frequency (MNF)} = \frac{\sum_{k=1}^{M} f_k p_k}{\sum_{k=1}^{M} p_k} \tag{Eq. B.3}
\]

\(p_k\) – Power spectrum at frequency \(k\); \(f_k\) – Frequency of the power spectrum at \(k\); \(M\) – Length of the frequency bin
Fig. C.1 is a representation of “bad” data. These data were not used for data analysis.
REFERENCES

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