Identification of Femoral-Acetabular Symptoms Using sEMG Signals During Dynamic Contraction

by

Zahra Karimi Tabar

A thesis submitted to The Faculty of Graduate and Postdoctoral Affairs
in partial fulfillment of the requirements for the degree of
Master of Applied Science in Biomedical Engineering

Ottawa–Carleton Institute for Biomedical Engineering (OCIBE)
Department of Systems and Computer Engineering
Carleton University

Ottawa, Ontario, Canada, K1S 5B6

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The undersigned recommend to
the Faculty of Graduate and Postdoctoral Affairs
acceptance of the thesis

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Chair, Roshdy H. M. Hafez, Department of Systems and Computer Engineering

Thesis Supervisor, Chris Joslin

Carleton University

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Abstract

This thesis focuses on development of an algorithm that automatically identifies a *Femoroacetabular Impingement* (FAI) patient from a healthy control person by comparing their *surface electromyography* (sEMG) signal recorded from *Gluteus Maximus* (GMax), *Tensor Fasciae Latae* (TFL), and *Rectus Femoris* (RF) muscles in the hip area. A *discrete wavelet transform* (DWT) method was used to analyze sEMG signals by thirty eight different *wavelet functions* (WFs) with 5 decomposition levels of dynamic contractions during the three phases (descending, stationary, and ascending) of squat task. The Bior3.9 WF was selected as it provided higher amount of energy for most of the subjects and then the wavelet power spectrum was computed for healthy control and FAI groups. The results show that the RF muscle is more active in the ascending phase than the descending phase for FAI subjects, whereas it is more active in the descending phase for healthy control. An independent sample t-test was used to check the activities of muscle in both groups. The results demonstrate no significant difference for GMax ($p=0.7477$) and TFL ($P=0.4997$) muscles, while there is a significant difference for RF muscle ($p=0.0670$).

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Acronyms

ANN	Artificial Neural Network
AP	Action Potential
AR	Auto-Regressive
BF	Biceps Femoris
BMI	Body Mass Index
CF	Center Frequency
CI	Co-activation Index
CWD	Chio-Williams Distribution
EMG	Electromyography
FAI	Femoroacetabular impingement
FFT	Fast Fourier Transform
FMF	Fourier Mean Frequency
FT	Fourier Transform
GMax	Gluteus Maximus
GRNN	General Regression Neural Networks
HHD	Hand-Held Dynamometer
IEMG	Integrated EMG

MDF	Median Frequency
ME	Myoelectric
MLP	Multilayer Perceptron
MM	Mechanomyographic
MMP	Multi-Muscle Pattern
MPF	Mean Power Frequency
MRI	Magnetic Resonance Imaging
MU	Motor Unit
MUAP	Motor Unit Action Potential
MVIC	Maximum Voluntary Isometric Contraction
NN	Neural Network
PCA	Principal Component Analysis
PSD	Power Spectral Density
RBF	Radial Base Function
RF	Rectus Femoris
RMS	Root Mean Square
sEMG	Surface Electromyography
ST	Semitendinosus
STFT	Short-Time Fourier Transform
TFL	Fasciae Latae
WF	Wavelet Function
WMF	Wavelet Mean Frequency
WT	Wavelet Transform
WVD	Wigner-Ville Distribution

Chapter 1

Introduction

Femoroacetabular Impingement (FAI) is a pathomechanical process where the human hip can fail. FAI usually appears in young and active adults with pain in groin area, although many FAI patients have no history of hip disease [7, 8]. Abnormalities of hip bones can damage the soft tissue structures and limit the patients' motion. Useful information can be achieved from the muscles and such information has clinical and engineering applications by measuring Electromyography (EMG) signals. EMG is a biomedical signal that provides a great source of information to clinicians and researchers by measuring the electrical currents generated in muscles during its contraction [9]. The EMG signal which is a complex signal is controlled by nervous system and the physiological and anatomical properties of muscles can influence on it [10].

In this thesis, we are interested in the developing of an algorithm to discriminate a FAI patient from a healthy person by comparing their EMG signal recorded from hip muscles. As a result, this introduction chapter is divided as follows: The first

sub-section will provide background information on relevant topics. Then, the problem statement will be exposed followed by the research objectives and the proposed methodology. Finally, the main contributions will be outlined and an overview of the remaining parts of the thesis will be given.

1.1 Background

In this part, we first review the anatomy of hip joint followed by information about FAI. Then, the concept of muscle contraction based on muscle physiology will be discussed. Finally, we express the methods to detect EMG signal from the muscles.

1.1.1 Anatomy of the Hip Joint

The structure of hip can be divided into four categories as follow:

- **Bones and joints:** The hip bones are the femur and the pelvis as shown in Figure 1.1. The top structure of the femur is like a ball and it is called the femoral head. The femoral head fits into the acetabulum which is a round socket. Thus, the hip joint is a ball (femoral head) and socket (acetabulum which is a part of the pelvic bone) joint to support the standing, walking, and running posture of the body. The femoral head and the surface of the acetabulum are covered by articular cartilage which creates a smooth, low friction surface. Moreover, the articular cartilage enables the femoral head and acetabulum slither easily [3]. The hip joint has three degree of freedom motions which means it moves in the three various planes including sagittal (flexion/extension), frontal (abduction/adduction) and transverse (external/internal rotation) planes. Therefore,

a wide range of movement depends on the hip joint.

Figure 1.1: A Healthy Hip, Femoral Head Fits into the Acetabulum [1]

- **Ligaments and tendons:** Three major ligaments connect bones to other bones and prevent excessive movement and dislocation, stabilize the hip joint. The iliofemoral ligament is the strongest capsular ligament which tightens on hip extension and external rotation of the hip [11]. The pubofemoral ligament tightens in hip extension and abduction and controls external rotation. The ischiofemoral ligament tightens on hip extension and restricting internal rotation [12].
- **Nerves:** The hip consists of two main nerves; the femoral nerve in front and the sciatic nerve in back. Also, there are many small nerves called obturator nerves. The function of these nerves is to carry the signals from brain to muscles

(move the hip) also carry signals back to brain from muscles.

- **Muscles:** Hip muscles are divided into four different groups according to their position named gluteal, lateral, adductor, and iliopsoas that control the movement of the hip. Figure 1.2 illustrates the most significant muscles in hip area.

Figure 1.2: Muscles in Hip Area [2]

1.1.2 Femoroacetabular impingement

FAI is a pathologic condition in which the femoral head and acetabular socket rub abnormally in the hip joint [13]. This abnormality reduces range of movements and performance in patients [3]. FAI usually appears in young and active adults with pain in groin area, although many FAI patients have no history of hip disease [7]. The physical activity and exercise may aggravate the pain in FAI patients [3].

FAI has two common forms known as cam impingement and pincer impingement however, the combination of both types is more common. Figure 1.3 indicates the diagram of the normal hip (a), hip with cam impingement (b), hip with pincer impingement (c), and the combination of cam and pincer impingement (d).

Figure 1.3: FAI Forms [3]

Cam Impingement, the femoral deformity, is an abnormality of the femoral head-neck junction where the femoral head is not round and cannot rotate smoothly inside the acetabulum. Therefore, the cartilage inside the acetabulum is grinded. Pincer impingement, the deformity on the acetabular side, is the situation where abnormality of the acetabulum causes impingement whereas the femoral head is morphologically normal [3, 14].

1.1.3 Skeletal Muscle Physiology

An overview of skeletal muscle structure is indicated in Figure 1.4.

Figure 1.4: Overview of Skeletal Muscle Structure [4]

The most prominent constituent of the muscle fiber is *myofibril* which is responsible for causing muscle cell contraction. Myofibrils have a contractile unit called *sarcomere*. The internal structure of the myofibril is composed of thick filaments (*myosin*) and thin filaments (*actin*). The myosin filaments have cross-bridges that are able to attach temporarily to the actin filaments. The sarcomeres consist of sev-

eral regions such as dark bands (A bands), and light bands (I band), and the ends of each sarcomere are defined by Z disc. The A and I bands related to the present or absence of myosin filaments. This means the I bands comprise only the actin filaments, whereas the A bands consist of myosin filaments. At the middle of A band there is a region called the H zone which includes only the myosin, however in peripheral regions of A band the myosin and actin overlap.

During muscle contraction, the actin filaments slide past the myosin filaments toward the middle of the sarcomere. In this situation, sarcomere shortens by the Z discs become closer to one another. The region for A band does not change, whereas both I and H zone almost disappear. Figure 1.5 indicates the sliding-filament model of muscle contraction [15].

Figure 1.5: Sliding-Filament Model of Muscle Contraction

1.1.4 EMG Signals

The electrical activity in the muscles arises from the contraction of the muscle fibers. The EMG signal is the sequence of voltages recorded from a contracting muscle over time. The muscle signal called *myoelectric* (ME) signal that is detected via EMG by using electrodes. This signal is composed of the *action potentials* (AP) traveling across the muscle fibers and each of these APs occur at random intervals. The muscle fibers are innervated in groups by α -motoneurons. Furthermore, a single α -motoneuron and the muscle fibers it innervates called a *Motor Unit* (MU) [16]. Figure 1.6 shows the motor unit and its components [17].

Figure 1.6: Motor Unit

MUs and the α -motoneurons vary in size. Small motoneurons innervate relatively few muscle fibers, while large motoneurons innervate larger amount of fibers. MUs also differ in the types of muscle fibers that they innervate. Generally, the small MUs are called *slow* motor units (type I), innervate small muscle fibers that contract slowly and generate small forces. These slow MUs are important for activity that require sustained muscular contraction. The *fast fatigable* motor units (type IIB) are significant for brief exercise which require large forces. The *fast fatigue-resistant* motor units (type IIA) have intermediate size and are not quite as fast fatigable

MUs. The fast fatigue-resistant MUs are substantially more resistant to fatigue and generate about twice the force than a slow motor units.

The *motor unit action potential* (MUAP) can be detected by invasive and non-invasive methods. In the invasive method, electrodes are inserted through muscle tissue (wire or needle electrode), whereas in the non-invasive method the electrodes are placed on the surface of the skin (surface electrode) on top of the muscle. The recorded signal called “raw EMG” has noise and it is normally a function of time.

The *surface electromyography* (sEMG) is a non-invasive technique that has potential usage in sports and rehabilitation medicine. Studying EMG signals can assess us to control the muscles performance in daily tasks and obtain information about the movement of the muscles.

1.2 Problem Statement

FAI is common in high level athletes , but also occurs in active individuals. FAI can be diagnosed using plain x-ray films to determine the shape of the femoral head and acetabulum as well as to indicate the amount of joint space in the hip. *Magnetic resonance imaging* (MRI) of the hip also can be used to confirm the damage to the joint. These methods are useful for diagnosing FAI based on bone deformation; however FAI patients may have abnormality in their hip muscles compared to a person without FAI.

Electrical activity of muscle provides significant information for physicians and doctors. The muscle activity can be measured between the FAI and healthy controls in order to assists physicians to diagnose FAI based on EMG activity of muscles.

In this thesis, the goal is to detect FAI in people based on the analysis of their EMG signal. Most analysis methods proposed in literature deal with different muscles in the body; however none of the studies consider the hip muscles for FAI people. Thus, the overall aim of this project is to develop an algorithm to automatically distinguish between FAI and healthy controls based on analysis of sEMG signals from hip muscles.

The outcomes of this study are important in terms of diagnosis of FAI patients based on their muscle activities instead of just considering the bone deformation. Using electrical activity of muscles for diagnosis of FAI can be a complement to MRI and x-ray methods.

1.3 Research Objectives

The main objective of this thesis is to develop an algorithm based on recorded EMG signal from three different muscles in hip area in order to discriminate FAI patients from healthy subjects. More specifically, we aim to:

1. Compute the signal's linear envelope for amplitude analysis of the EMG
2. Calculate integrated EMG and discriminate between groups
3. Develop approximate algorithms based on computing energy of EMG signals using wavelet transform methods and select a wavelet function to distinguish FAI from healthy control
4. Develop wavelet power spectrum of EMG signals and compare the performance of the algorithm

1.4 Methodology

The EMG signal is a complex signal which contains valuable information. Different signal processing methods are applied on raw EMG in order to attain the actual EMG signal. Discriminating the FAI and healthy control groups is an exhaustive task, as the variability between them is high and it is hard to differentiate the groups. The methodology used to approach the solution in this thesis is described below:

1. *Using signal processing methods:* Signal processing methods were used to obtain the actual EMG from the raw EMG.
2. *Study wavelet transforms:* In order to acquire a good knowledge about decomposition of EMG signals, the wavelet transform was studied and compared with other time-frequency methods.
3. *Select a wavelet function for our EMG signals:* Reviewing the literature on wavelet transform reveals that there is not a specific method to choose a wavelet function so far. In order to select a wavelet appropriate for our sEMG signal, various wavelet families are required to be considered.
4. *Calculate the energy from various wavelet families:* Applying various wavelet functions to EMG signals and selecting the one that gives the highest amount of energy for most of signals.
5. *Implement algorithm:* The wavelet transform method was used to solve the thesis problem. Due to high variability between FAI and control groups, we used MATLAB programming language to calculate the wavelet power spectrum.

6. *Discriminate FAI from healthy controls:* The problem was solved by wavelet transform method. The power of signals were calculated and compared together. Finally, the efficiency of time-frequency methods to solve the thesis problem were investigated and analyzed.

1.5 Contribution

The main contribution of this thesis is summarized as follows:

1. *Identification of Femoral-Acetabular Symptoms Using sEMG Signals During Dynamic Contraction:* An algorithm for discriminating the FAI from healthy control was proposed and analyzed. As the wavelet transform represents a very suitable method for the classification of EMG signals, this time-frequency method was used in this algorithm. The wavelet analysis has an advantage over FFT which provides the frequency contents of the signal over the time period that is being analyzed. As the shape of the wavelet and MUAP is related to a better decomposition, wavelet analysis was chosen to match the shape of the MUAP, and the results yield the best possible energy localization in time-scale plane. In this algorithm we decomposed sEMG signal from Gluteus Maximus, Tensor Fasciae Latae, and Rectus Femoris muscles using discrete wavelet transform for different wavelet functions and calculated the energy during dynamic contraction in squat task. A wavelet function which provided the highest amount of energy in most of our subjects was selected. Furthermore, the wavelet power spectrum was computed and used for discriminating the FAI patients from the healthy controls. The results of this work will be submitted

to a journal paper.

1.6 Thesis Overview

The remainder of the thesis is organized as follows. In Chapter 2, we present a selective review on muscle weakness in FAI patients and time-frequency analysis methods. In Chapter 3, we present the proposed methodology and algorithms used in this work. In Chapter 4, we present the simulation results and discriminate FAI and control groups. In Chapter 5, we conclude the work and suggest future directions.

Chapter 2

Literature Review

2.1 Background

The EMG signal is a complicated signal which is controlled by nervous system. The anatomical and physiological properties of muscles have influence on the recording of the EMG signal. Moreover, the EMG signal can be affected by various external factors varying its shape and characteristics. Some of these factors are tissue feature, physiological cross talk, changes in the geometry between muscle belly and electrode site, external noise, and electrode and amplifiers [18].

An EMG signal recorded from muscles requires advanced methods for detection, decomposition, processing, and classification. In order to use the EMG signal as a diagnosis signal, a feature is extracted before analysis or classification of it. This is due to the fact that the raw EMG signal includes both useful information and noise. EMG features can be computed in various domains such as time, frequency, time-frequency, and time-scale domains. Analysis of EMG data requires rectification and

integration of signals or root mean square values to extract information related to the amplitude of the signal which deals with the time domain representation. However, the frequency content of EMG is analyzed using *Fourier Transform* (FT) that is a uni-dimensional technique. Moreover, a signal can be stationary or non-stationary. If a signal is stationary, its properties are statistically invariant over time; however the transient events cannot be predicted in non-stationary signals. The EMG signal is a non-stationary signal, thus FT and other classical signal processing methods are not suitable for analyzing EMG signals recorded during dynamic conditions. Furthermore, time-frequency methods that are appropriate for non-stationary signal are used instead of frequency methods to improve the EMG analysis [19]. Thus, for analyzing EMG signals in both time and frequency, the *short-term Fourier transforms* (STFT) and wavelets can be accomplished. The processing of the EMG signals usually has three steps: recording the EMG signals, decomposition of signals by signal processing techniques, and classification of signals for diagnostic purpose.

In this chapter, first a literature review in the area of muscle weakness in FAI patients is presented. Then, time-frequency analysis method is discussed in detail. Finally, the best method in analyzing the EMG signals is presented as well as the related works in literature.

2.2 Muscle weakness in FAI

FAI is a pathomechanical process which causes hip pain and disability in people. It is the deformity of bones that leads to joint damage and pain. FAI patients experience functional disability during dynamic activities that can be related to the weakness

of the hip muscles. Although there are not many studies on muscle weakness in FAI patients, the few existing studies demonstrated the relationship of hip muscles. Casartelli et al. [20] attempted to compare hip muscle strength and hip flexor electromyography activity between symptomatic FAI patients and healthy controls. They stated the overall hip muscle weakness in symptomatic FAI patients. Isometric *maximum voluntary contraction* (MVC) strength of the hip muscles in three planes (sagittal, frontal, and transverse) was measured unilaterally. Muscle weakness was quantified by comparing strength outcomes between FAI patients and healthy controls. Hip abduction, adduction, internal rotation, and external rotation were randomly tested first. Then, the hip flexion and extension were determined in a randomize order. Hip abduction, adduction, internal and external rotation MVC strength evaluated with hand-held dynamometry, is a portable device which measures strength during manual muscle testing. In addition, hip flexion and extension MVC strength determined with isokinetic dynamometry in order to concurrently record MVC torque and EMG traces. Also, in a subgroup, the muscle activity of two main hip flexor muscles including the *Rectus Femoris* (RF) and *Tensor Fasciae Latae* (TFL) was measured by using EMG during active flexion. The highest MVC was considered in each muscle groups and for better distinguishing muscle weakness, the percentage difference in MVC strength was calculated. Casartelli et al. also recorded the EMG signal from RF and TFL muscles during muscles contraction. In general, they affirmed that the MVC was significantly lower in symptomatic FAI patients compared to healthy controls for hip adduction, flexion, external rotation, and abduction. Moreover, FAI patients presented lower EMG activity in TFL muscles than healthy controls. Furthermore, one year after their first paper, Casartelli et al. [21] expressed that the symptomatic FAI

patients have hip muscle weakness especially in hip flexion and hip adduction. They postulated in alignment to hip flexor muscle weakness, FAI patients have greater hip flexor fatigue than healthy controls. For considering the hip flexor fatigue, they performed two experiments. In the first experiment, the hip flexor torque fluctuation and EMG activity were recorded simultaneously during continued submaximal isometric contraction for RF and TFL muscles. In order to evaluate fatigue, the average hip flexion torque fluctuation, average EMG *root mean square* (RMS) and *median frequency* (MDF) were calculated. In the second experiment, hip flexor torque decline was assessed during a maximal dynamic contraction. Then, the weight-normalized isokinetic torque and the rate of torque decline were calculated. As a result, Casartelli and his collages proved that under isometric and isokinetic situation FAI indicates hip flexor weakness. In addition, Mantovani et al. [22] analyzed a group of hip muscles during squat in order to calculate the co-activation index (higher co-activation index causes stiffness in the joint and enhance joint contact loading) for FAI patients and compared that to healthy controls. They believed that the symptomatic FAI patients had higher muscle co-activation levels compared to asymptomatic FAI and controls. They considered three groups of unilateral symptomatic FAI, unilateral asymptomatic FAI, and control. The contribution of a group of muscles including *Gluteus Maximus* (GMax), *Biceps Femoris* (BF), *Semitendinosus* (ST), TFL, and RF muscles were evaluated by recording EMG activity based on SENIAM guidelines. The *co-activation index* (CI) which showed the contribution of a group of muscles was estimated during descending and ascending phase for both affected and unaffected sides. They concluded that the high muscular co-activations were indicated in the affected side for the asymptomatic FAI group.

In general, the muscle weakness in FAI can be obtained by considering the activity of each hip muscle separately or by evaluating the interaction between hip muscles.

2.3 Time-Frequency Analysis Methods

Traditional techniques for analyzing surface EMG signal are based on the FT method. The accuracy and reliability of this technique depends on the data lengths' and the signal requires to be stationary. In daily life activities or movements, subjects perform more dynamic contractions instead of isometric contractions. Moreover, in the field of rehabilitation medicine, sports medicine, and etc., tasks similar to daily activities are performed. During dynamic conditions, the Fourier and other classical signal processing methods are not suitable for analyzing the *myoelectric* (ME) signals as a number of active motor units, active muscle fibers, electrode geometry, muscle fiber lengths, and innervation zone geometry changes. These factors emphasize that the ME signals are non-stationary. Therefore, time-frequency methods have been introduced for the analysis of non-stationary signals. These time-frequency representation methods are the STFT, *Wigner-Ville distribution* (WVD), *Choi-Williams distribution* (CWD), and *wavelet transform* (WT) that were compared with recent studies for accuracy and precision to analyze the ME signals [19,23].

Gabor [24] developed the STFT method based on Fourier transform method. The input signal was divided into segments and the signals in each window were stationary. The STFT analyzed the signal with fixed resolution and mapped the distribution of the energy of the signal in the time-frequency plane which was called *spectrogram* [5].

WVD can be used as a time-frequency energy distribution method which intro-

duced by Wigner and then modified by Ville in order to be applied to the signal processing field [25]. Duchne et al. [26] used WVD method for analyzing uterine EMG in order to track instantaneous burst frequency. In this method the instantaneous frequency was equivalent to the mean frequency. The result delivered by Duchne et al. confirmed that converting the ME signals to the time-frequency plane by applying WVD method to the ME signals was approving the relationship between sEMG and electrical activity of the uterine muscle at a cellular level. Furthermore, Knaflitz et al. [27] used Wigner-Ville transform to evaluate muscle fatigue during dynamic contractions. The instantaneous mean frequency was reduced and this phenomenon caused the muscle fatigue. The reduction in frequency was related to the decrease in velocity of depolarization of propagation along the muscle fibers. The result was a low time-resolution associated to body movement. Thus, the Wigner-Ville transform was not a suitable method to deal with multi component signals.

Bonato et al. [28] analyzed the ME signals during dynamic contractions. They compared different time-frequency methods such as the WVD, reduced interference, cone kernel and CWD by using different types of kernels. As a result, they proposed that the CWD was the most appropriate time-frequency method for analyzing the non-stationary ME signals in a dynamic contraction.

A time-frequency analysis based on wavelets [29] which is introduced recently is an appropriate tool to overcome the limitations of the traditional time-frequency methods. Karlsson (2000 and 2001), introduced the wavelet transform as a “mathematical microscope” that help observe various parts of the signal by setting the focus [19, 23]. The WT has some advantages over the other time-frequency methods. As represented in Figure 2.1, the WT uses short window for high frequencies and long

window for low frequencies, although the STFT uses a single analysis window for all frequencies [5]. Furthermore, the WT can be used to analyze both stationary and

Figure 2.1: Time-Frequency Plane in STFT and WT [5]

WT method recently introduced overcome other time-frequency methods due to high performance and advantages. The wavelet theory covers both the continuous and discrete time cases. In the following sub-sections, wavelet transforms will be explained. The continuous and discrete WT will be introduced and their specifications will be discussed. Wavelet types and families will be presented following by choosing a wavelet for analyzing EMG signals. Also, different studies that have used WT to analyze EMG signals are explained.

2.3.1 Wavelet Transforms

Historically, the concept of *wavelets* developed mostly in the early 1980s. This new concept is connected to many fields including mathematics, physics, computer science, and engineering. The history of mathematics leading to Wavelets began with Joseph Fourier (1807) with the theory of frequency analysis. He believed that functions can be represented as the summation of sines and cosines. Also, Joseph delivered the idea of Fourier Transform, which transforms a function in time domain into a new function in frequency domain. The first presentation of wavelets appeared by Alfred Haar in 1909. The Haar wavelets are the simplest of the wavelet families and are not continuously differentiable which limits their applications. Jean Morlet around the 1975 used the term wavelet to define his functions. In 1982, Morlet discovered the idea of wavelet transform. He believed that keeping the window fixed when using windowed Fourier analysis was not an appropriate approach. Thus, Morlet changed the window while the frequency of the function was kept constant. Based on his finding, stretching the window stretched the function and squeezing the window compressed the function. In late 1986, Yves Meyer and Stephane Mallat discovered the multi-resolution analysis for wavelets. In 1988, Ingrid Daubechies used the multi-resolution analysis idea in order to produce the Daubechies families of wavelets [30]. The Daubechies wavelets have compact support, orthogonality (the inner products of all of the different translates are zero), regularity (can produce linear functions), and continuity.

Wavelets are functions that oscillate above and below the x-axis and have varying frequency, limited duration, and an average value of zero [31]. Wavelets are localized

in time-frequency space and wavelet transformation has been used for the processing of signals which are non-stationary and time varying. Each wavelet is represented by a bell shaped filter curve which has a center frequency at the point of maximal amplitude and a mode parameter that controls the bandwidth of the wavelet. The WT is achieved by a convolution of wavelets with the EMG signal. This convolution can be performed in time or frequency space. Wavelets have an automatic adapt window in order to give the appropriate resolution. The size of this window is not fixed and varies with frequencies; short/narrow window for high frequencies and long/wider window for low frequencies [19, 32]. Therefore, wavelets are used to focus on short time intervals for high frequency components and long time intervals for low frequency components and this property improves the signal analysis. A new approach for the analysis of EMG signals was developed by von Tscharner [31] using a filter-bank of non-linearly scaled wavelets. According to von Tscharner (2000), wavelets can be represented in time or frequency space for the intensity analysis. Thus, wavelets as functions of frequency are defined by center frequency and scale parameters. Tscharner described a time-frequency analysis of the intensities in time series. He used a filter bank of non-linearly scaled wavelets for this purpose. The intensity was calculated in order to approximate the power of the signal in time. The result of his research was the intensity patterns extracted from the EMG signal. Tscharner stated that the wavelet analysis method had an advantage over analyzing EMG by root mean square and averaging rectified signals. By using wavelet analysis method, the intensity analysis did not eliminate the higher frequency components compared to two other methods. Furthermore, in wavelet space the intensity indicates all power aspects of the signal and its variation in time and frequency. Based on

Barandum et al. [33], the demonstration of the intensity versus center frequencies of the wavelets provided a wavelet spectrum. Also, an intensity pattern which was called a scalogram was represented by three dimensional graph of the intensity versus time and center frequency. Rioul et al. [5] also stated that by applying wavelets the signal is mapped into a time-scale plane, which is equivalent to a time-frequency plane in STFT. This time-scale plane is called scalogram, which indicated the distribution of the energy of the signal.

The WT is classified into continuous wavelet transforms (CWT) and discrete wavelet transforms (DWT). CWT is used for signal analysis and operates over every possible scale and translation, whereas DWT is used for data compression and uses a specific scale and translation values.

2.3.1.1 Continuous Wavelet Transform

In wavelet analysis, the wavelet family consists of enlarged or compressed version of the basic function as well as translation. When the input signal is $x(t)$, the equation for *continuous wavelet transform* (CWT) is as follows:

$$CWT(a, b) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{|a|}} \varphi * \left(\frac{t - b}{a} \right) dt \quad (2.1)$$

where a is the scale parameter, b is the translation or time shifting parameter, and ϕ is a basis function or wavelet function. The $*$ donates complex conjugation and the factor $\frac{1}{\sqrt{|a|}}$ is introduced for energy normalization [5, 32, 34].

The wavelet coefficients, $CWT(a, b)$, indicate the correlation between signal and the basis function at different translations and scales. With a large a , when the basis

function is stretched, the low frequency components of the signal can be analyzed. With a small a , when the basis function is contracted, the high frequency components of the signal can be analyzed.

The CWT generates more coefficients than are actually required to specify the signal. In other words, it provides an oversampling of the original signal. For analysis applications, this oversampling is not a serious problem; however the redundancy will be costly if the original signal needs to be recovered. Therefore, when the recovery of the original signal is significant, the *discrete wavelet transform* (DWT) is used to restrict the variation in translation and scale [34].

2.3.1.2 Discrete Wavelet Transform

The DWT is introduced in terms of its recovery transform through the following equation:

$$x(t) = \sum_{k=-\infty}^{\infty} \sum_{l=-\infty}^{\infty} d(k, l) 2^{\frac{-k}{2}} \varphi(2^{-k}t - l) \quad (2.2)$$

where k is related to a by ($a=2^k$), and b is related to l by ($b=(2^k l)$). Also, $d(k, l)$ is a sampling of $CWT(a, b)$. The DWT has the scaling function which is defined as the following equation:

$$\Phi(t) = \sum_{n=-\infty}^{\infty} \sqrt{2}c(n)\Phi(2t - n) \quad (2.3)$$

where $c(n)$ is a series of scalars which relates to specific scaling function. The wavelet can be defined based on the scaling function as the following equation:

$$\varphi(t) = \sum_{n=-\infty}^{\infty} \sqrt{2}d(n)\Phi(2t - n) \quad (2.4)$$

where $d(n)$ is a series of scalars which is associated with $x(t)$ from equation 2.2. Thus, the DWT can be implemented using equation 2.4 based on filter bank technique [34].

A very useful implementation of DWT called *multi-resolution* analysis is indicated in Figure 2.2. The original sampled signal $x(n)$ is passed through high-pass and low-pass filters that are shown by $h(n)$ and $l(n)$, respectively. The output of both high and low pass filters are decimated by 2 to achieve the *detail* (D_1) and *approximation* (A_1) coefficients. The approximation coefficients are passed through the second step in order to repeat the process. Therefore, the signal is decomposed according to the required levels. In Figure 2.2, the signal is decomposed at 3 levels [5].

Figure 2.2: Wavelet Multi-Resolution Analysis [5]

During a typical wavelet analysis, wavelets of various lengths are applied to a

particular signal. Then, the portion of the signal which is correlated with the shortest length (D1 which is first detail) is subtracted away. This means that the high frequency components which are representing the noise are removed. According to Figure 2.2, the filtering process splits the signal into high frequency (detail, D) and low frequency (approximation, A) bands [35]. The signal is downsampled in order to avoid doubling the number of data points at each level.

2.3.2 Wavelet Types and Families

There are different types of continuous and discrete wavelets available. The wavelet transform requires the selection of a mother wavelet depending on the application.

2.3.2.1 Properties of Wavelet Functions

Wavelets are defined by the scaling function (also called father wavelet) and wavelet function (or the mother wavelet). The scale function in WT determines wavelet dilation and compression of the various wavelets from a mother wavelet. Furthermore, the optimization of the WT is related to the scale function which is used for a particular signal. In the following, each wavelet families are introduced by representing their scaling and wavelet functions.

- **Haar:** Haar is the simplest wavelet which is discontinuous and resembles a step function. It illustrates the same wavelet as Daubechies db1. Figure 2.3 shows the scaling and wavelet function of this wavelet.

Figure 2.3: Haar Scaling and Wavelet Function

- **Daubechies:** Daubechies are compactly supported orthogonal wavelets. This family has highest number of vanishing moments which is indicated by N and has an external phase. Figure 2.4 shows the db2 and db10 scaling and wavelet functions when using MATLAB software.

Figure 2.4: Daubechies 2 and 10 Scaling and Wavelet Functions

- **Symlets:** Symlets family are compactly supported wavelets with nearly symmetric and highest vanishing moments similar to Daubechies family. This family is a modification of db family and with similar properties. Figure 2.5 exhibits the scaling and wavelet functions of symlets 8.

Figure 2.5: Symlets 8 Scaling and Wavelet Functions

- **Coiflets:** Coiflets family has the scaling function of $2N-1$ moments equal to 0 and the wavelet function of $2N$ moments equal to 0. Figure 2.6 shows coif2 and coif5 scaling and wavelet functions.

Figure 2.6: Coiflets 2 and 5 Scaling and Wavelet Functions

- **Biorthogonal:** Biorthogonal family of wavelets illustrates the property of linear phase and includes two wavelets instead of one compare to other families; one for decomposition and the other one for reconstruction. Figure 2.7 illustrates the decomposition wavelet function which is significant in this research.

Figure 2.7: Biorthogonal Decomposition Scaling and Wavelet Functions

- **Morlet:** Morlet wavelet that is illustrated in Figure 2.8 has no scaling function.

Figure 2.8: Morlet Wavelet

- **Mexican Hat:** This wavelet has no scaling function similar to Morlet wavelet.

Mexican Hat wavelet function is represented in Figure 2.9.

Figure 2.9: Mexican Hat Wavelet

- **Meyer:** Meyer scaling and wavelet function is defined in the frequency domain.

This wavelet is represented in Figure 2.10.

Figure 2.10: Meyer Scaling and Wavelet Function

Frere et al. [36] considered the influence of the scaling function, polynomial and exponential functions on the WT. The mean frequency was calculated for each WT and the value was compared with the mean frequency for FFT. Also, the total intensity for both WT was compared with the root mean square. Frere et al. demonstrated that the choice of the scale function had a significant difference in time and frequency domains. The authors confirmed that a second-degree polynomial scale function, as was used in von Tscharner [31] research, was suitable to be used as a reference in wavelet processing of the EMG signal.

2.3.3 Choosing a Wavelet for EMG Signals

The ability of DWT to extract features from the signal is dependent on choosing an appropriate mother wavelet function. The common standard families of wavelet basis functions are *Haar*, *Daubechies*, *Coiflet*, *Symmlet*, *Morlet*, and *Mexican Hat*. Although there is not a specific rule for selecting a wavelet basis function, some features of wavelets cause a specific mother wavelet to be more appropriate for a particular application and signal type. According to Santoso et al. [37] state, for slow transients disturbances db8 and db10 wavelets were the best choice, whereas for short and fast transient disturbances db4 and db6 were more proper. Also, Walker [38] presented general guidelines for selecting a wavelet such that db4 was more appropriate for feature extraction and coiflet6 provided better data compression results. In order to select a more accurate wavelet function, it is significant that the characteristic of signal should be matched with the properties of the wavelet function.

For applying WT into the EMG signal various mother wavelets and scale functions can be used although no agreement has been reached regarding the selection of the mother wavelet and the scale function. For example, Karlsson et al. [32] used Morlet mother wavelet with linear scale function [23, 32, 39] and Neto et al. [40] applied Morlet with exponential function. Von Tscharnar [31], used Cauchy mother wavelets with polynomial function. Hostens et al. [41] and Beck et al. [42] applied Daubechies mother wavelets in the EMG signal with different scale functions. Hostens et al., used linear scale function while Beck et al. used dyadic function.

The WT of the EMG signal has been used in several studies related to muscle fatigue, EMG signal processing, and muscle strength. Moreover, Neto et al. [40, 43],

and von Tscharner et al. [31, 44–47], used the WT for the EMG signals that were recorded during the sports.

Flanders [48] used discrete wavelet transformation to identify time of occurrence of EMG bursts. He chose wavelet db2 and focused on the coefficient at the scale D3 because by plotting the peak to peak range of the db2 weighting coefficient values of several muscle, D3 component had the largest peak weighting coefficients based on his research. Thus, Flanders demonstrated that the simplest wavelet such as db2 was suitable for recognizing multiunit EMG bursts. Moreover, Kilby and Gholam Hosseini [49] also used mother wavelet that had different set of families to extract detailed features of the sEMG signals. They used mother wavelets that were available in LabVIEW® to decompose the sEMG signals and reconstruct the signal back. The reconstructed signals were subtracted from the original signals in order to calculate the errors. Based on different errors of the various families of the mother wavelets, they concluded the Daubechies (db5) was the most appropriate mother wavelet for analyzing sEMG signals. However, they did not consider several mother wavelets such as Morlet, Meyer, and Mexican Hat because these mother wavelets were not available by the software. Ahmed et al. [10] illustrated a comparative study of decomposing sEMG signals by using different types of wavelets. Their goal was to choose a wavelet based on the best possible energy localization in the time-scale plane. In their algorithm, they decomposed a signal using DWT for various wavelets and the energy localization in time-scale plane was calculated. From their results, db4, db5, and db6 indicated to have the highest energy compare to other wavelets for normal and healthy muscle EMG signal.

2.3.4 Different Studies using the Wavelet Transform

MUAP

Wavelet analysis is able to provide a new way in describing MUAP in the time-frequency plane. Guglielminotti and Merletti [50] theorized that in wavelet analysis, it was required to choose a wavelet which was the best match for the shape of the MUAP. The results of WT provided the best possible energy localization in the time-scale plane. Pattichis and Pattichis [51] utilized the WT to analyze signals at different resolution levels and this process was known as multi-resolution analysis. They considered the connection between wavelet coefficients and the time-frequency plane and found out how coefficients from one stage of the WT could be used to construct functional approximation to the original signal. In addition, Laterza and Olmo [52] proposed WT as an effective tool for the MUAP detection. They used the Mexican Hat wavelet because it matched with the shape of the MUAP, and the result of WT provided the best possible energy localization in time-scale plane. Also, Zennaro et al. [53] provided a decomposition method based on multichannel long-term recording of signal instead of single-channel recording. They believed that the wavelet coefficients of lower frequency bands were more important than higher bands for distinction of action potential characterization. They developed a software and believed that it is appropriate for the study of MU patterns and recruitment order in long-term recording of signal. However, the results from Yamada et al.'s [54] experiment indicated that the high frequency information was also significant in classifying MUAP. They applied *principal component analysis* (PCA) to wavelet coefficients in order to consider all frequency informations.

Fatigue

The EMG signal can be used to detect muscle fatigue. According to Luca [55], the fatigue was related to the various physiological and psychological phenomena. Fatigue is defined as a condition when the muscle's ability to contract and produce force is decreased. The frequency domain provides significant features of the EMG signal [56]. Therefore, in the frequency domain several variables of EMG power spectrum requires to be analyzed.

- **Mean frequency:** The *mean frequency* (MNF) is an average frequency which is defined as a sum of product of the power spectrum and the frequency over a total sum of the power spectrum [57,58]. Eq 2.5 shows the definition of MNF:

$$MNF = \frac{\sum_{j=1}^M f_j P_j}{\sum_{j=1}^M P_j} \quad (2.5)$$

- **Median frequency:** The *median frequency* (MDF) is a frequency value at which the EMG power spectrum is divided into two regions with an equal power. Eq 2.6 shows the corresponding formula:

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^M P_j = \frac{1}{2} \sum_{j=1}^M P_j \quad (2.6)$$

The MNF and MDF are used for stationary signals. When a muscle contracts during dynamic conditions, the EMG signal generated by the muscle should be considered as a non-stationary signal. Meanwhile, the analysis of the non-stationary signal requires the time-frequency spectrum. The instantaneous mean and median

frequency are derived by replacing the power spectrum with the time-frequency spectrum. Thus, the IMNF and IMDF are computed through following equations [59]:

$$\int_0^{IMDF(t)} S(t, f) df = \int_{IMDF(t)}^{\infty} S(t, f) df \quad (2.7)$$

$$IMNF(t) = \frac{\int_0^{\infty} f S(t, f) df}{\int_0^{\infty} S(t, f) df} \quad (2.8)$$

In general, the mean frequency can be extracted by applying a FFT or a WT. Various papers have been measuring or comparing the frequency from FFT and WT [31, 46, 60–66] to find the best method for analyzing the sEMG signals.

Constable et al. [67] analyzed sEMG signals from four muscles (soleus, vasti, gluteus maximus, and hamstrings) during dynamic contraction using continuous DWT based on 4-coefficient Daubechies wavelet. The results illustrated more high frequency activation at low levels and more low frequency activation at higher levels due to fatigue of fast twitch fibers.

Karlsson et al. [32] stated that the mean frequency was usually measured from power spectrum which was attained by a Fourier Transform. Moreover, the mean frequency could also be gained from a wavelet based power spectrum. Barandum et al. [33] affirmed the difference between using *Fourier Mean Frequency* (FMF) and a *Wavelet Mean Frequency* (WMF) when analyzing sEMG during early fatigue in isometric contraction. They demonstrated that the wavelet transform was able to measure the mean frequency in a shorter time period. In addition, Beck et al. [42] aimed to determine the *mechanomyographic* (MMG) and EMG center frequency (*mean power frequency* (MPF), *median frequency* (MDF), and wavelet *center frequency* (CF)) pat-

terns for biceps brachii muscle during fatiguing isokinetic actions by comparing FFT and DWT methods. For DWT, Beck used the Daubechies 4 (db4) wavelet algorithm. The DWT decomposed MMG and EMG signal into several scales (frequency bands) and the center frequency was defined after plotting the amplitude-frequency distribution. As a result, they found out that the mpf, mdf, and cf were the same for MMG and EMG. Also, the Fourier methods were suitable for providing the patterns for normalized MMG and EMG center frequency during fatiguing dynamic muscle actions. Karlsson et al. [23, 32] reported that the WT was more accurate for determining the EMG power spectrum and produced mean frequency evaluated which has less noise compare to the estimates from the FT. Moreover, Kumar et al. [65] used WT for diagnosing fatigue. They proposed that the WT decomposed the signal into several multi-resolution components based on wavelet function when the sampling rate is 5 kHz. They used WT with various WF to decompose the sEMG signal and the output power was calculated. According to the output power parameter, Kumar et al. chose the WF that provided the best contrast between non-fatigue and fatigue sEMG signals. They believed that the difference between non-fatigue and fatigue muscles was emphasized when sym4 and sym5 wavelet functions were used. The muscle fatigue using sym4 and sym5 at level 8 and 9 (out of 10) of wavelet decomposition could be determined by applying WT to sEMG signals.

Classification of EMG signal

Gheab et al. [68] presented a method to analyze different EMG signals by studying the coefficients of fifteen wavelet families after passing the training and validated in the *neural network* (NN). They considered the EMG signal that was recorded from right pectoralis, right biceps, and right triceps muscles for three volunteers when

performing the butterfly exercises with 5 lb and 10 lb. Their work comprised of using WT technique and applying *Artificial Neural Network* (ANN). WT was used to generate denoised and compressed EMG signal and ANN was applied for feature extraction and classification. They concluded that Haar and db in level 4 and 5 were more comfortable to be used with the recorded EMG signal. In addition, Ozsert et al. [69] proposed methods to classify biceps, frontalis, and abductor pollicis brevis muscles after recording EMG signals. They reduced the size of EMG signals by using the WT (pre-process EMG signals) and an *auto-regressive* (AR) method. The three ANN types were used for classifying EMG signals such as *multilayer perceptron* (MLP), *radial base function* (RBF), and *general regression neural networks* (GRNN). The AR coefficients were used for training and testing MLP, RBF, and GRNN. Ozsert et al. showed that the classification accuracy of the pre-processed data set was higher compared to unprocessed data set for MLP and GRNN systems.

Von Tscharner analyzed EMG signals based on the wavelet transform [31] and produced intensity patterns of the EMG signal. Von Tscharner and Goepfert [45] combined the intensity patterns into a *multi-muscle pattern* (MMP) and represented it in a pattern space that is a vector space. Then, Von Tscharner used the spherical classification to classify the EMG intensity patterns [70]. As a result, an optimal dimensionality for the pattern space was required at which the spherical classification worked best. If the dimensionality was fixed too low, a pattern space was unable to reproduce the patterns with details. Furthermore, limiting the dimensionality decreased the noise in the reproduced patterns and improved classification.

Chapter 3

Methodology

This chapter presents the proposed methodology for analyzing EMG signals to identify healthy controls and FAI patients. It also refers to the procedures done to the signals for pre-processing, processing and analyzing the EMG signals.

Figure 3.1 provides a schematic description of the steps discussed in this research. In the first step, the raw EMG was processed by generating the EMG linear envelope which was provided based on normalization, full-rectified, and low-pass filtering. This process gave useful results for analysis. Then the integrated EMG was calculated for comparison. In the second step, the wavelet transform method was applied to the normalized EMG signals. Different wavelet functions were applied and their wavelet coefficients were calculated. One of the wavelet functions that provided the highest energy was selected. The third step of this producer was to calculate the wavelet power spectrum from the wavelet coefficients of the selected wavelet function.

Figure 3.1: Schematic Description of the Technique

3.1 Recording Process for EMG Signals

The EMG data of *Gluteus Maximus* (GMax), *Tensor Fasciae Latae* (TFL), and *Rectus Femoris* (RF) muscles were recorded from 30 subjects during dynamic contraction

of squat task (Figure 3.2). During squat, subjects were required to stand with feet shoulder-width apart, parallel to one another. Both arms were anteriorly extended, and heels were in contact with the floor during the entire squat. Five repetitions of the same movement were executed [6]. The recorded sEMG signals formed two groups: control and FAI. The control group consisted of 15 males and 1 female whereas FAI group contained 11 males and 3 females. The file which was a structure array contained the data for all the subjects who belonged to control (CON) and FAI pre-surgery patients (OR). The FAI group was named OR in this file as the patients were waiting for surgery.

Figure 3.2: Descending, Stationary, and Ascending Phase of Squat [6]

Participant characteristics are indicated in Table 3.1.

Table 3.1: Participant Characteristics by Group

Group	Gender	Weight (Kg)	Height (cm)
Control (CON) Subjects			
1	M	104.591	191.2
2	M	132.009	179
5	M	113.527	176
6	F	97.245	152
7	M	120.189	180.5
10	M	93.078	175.5
11	M	83.666	180.5
12	M	87.466	168
15	M	117.896	177.5
17	M	83.551	178
19	M	83.311	181
20	M	106.529	183
22	M	82.646	177
23	M	147.725	176
24	M	61.129	160.5
25	M	79.526	175.5
FAI (OR) Subjects			
3	M	129.012	183.75
4	M	83.035	168
8	M	139.491	186
9	M	133.394	176.5
13	M	126.997	174.2
14	M	101.154	175
16	M	108.719	175
18	M	149.428	176
21	F	97.508	163
26	M	64.312	167
27	M	136.712	167
28	M	120.632	175
29	F	132.507	168.5
30	F	59.766	167

3.2 EMG Data Processing

Raw EMG signals were recorded from GMax, TFL, and RF muscles had a zero hertz (DC) offset, therefore the DC offset was removed from each raw EMG signal by using *detrend* function which removes linear trend from the matrix. In order to be able to compare the EMG activity in the same muscle on different subjects, the EMG signals have to be normalized. Normalization of EMG signals were performed by dividing EMG signals during a squat task to a reference EMG value achieved from the same muscle of the same subject. There are various normalization methods available to do so and choosing between them is critical as it can influence the amplitude and pattern of EMG signals [71]. However, there is not a completely optimized method for normalization of EMG signals therefore, a variety of methods have been used to gain the normalization reference values. In this research we utilized MVIC method for normalization. In order to measure the MVIC the participants were asked to lie down on a testing bench, which was provided with support beams and adjustable straps to limit the movement of the limbs and hold it in place during isometric contraction. The MVIC were collected for duration of 5 seconds for each muscle. MVICs for GMax and RF muscles were measured when the participants leg was straight, and they were asked to push upwards against the *Hand-Held Dynamometer* (HHD). Moreover, MVIC for TFL muscle was collected when the participants were asked to push diagonally against the HHD. The MVIC values of participants for three muscles are indicated in Table 3.2.

Table 3.2: Participants' MVIC Values for GMax, TFL, and RF Muscles

Subjects	MVC		
	GMax (muscle 1)	TFL (muscle 2)	RF (muscle 3)
1	$7.91E^{-2}$	$4.26E^{-1}$	$2.37E^{-1}$
2	$6.20E^{-2}$	$3.74E^{-2}$	$1.16E^{-1}$
3	$7.28E^{-2}$	$3.78E^{-1}$	$1.18E^{-1}$
4	$3.95E^{-4}$	0	$2.52E^{-4}$
5	$5.51E^{-2}$	$7.02E^{-2}$	$1.14E^{-1}$
6	$5.40E^{-2}$	$1.74E^{-1}$	$9.17E^{-2}$
7	$5.10E^{-2}$	$1.03E^{-1}$	$5.31E^{-2}$
8	$1.31E^{-4}$	$1.35E^{-4}$	$3.03E^{-4}$
9	$2.88E^{-4}$	$1.04E^{-4}$	$1.94E^{-4}$
10	$7.34E^{-5}$	$3.55E^{-4}$	$1.96E^{-4}$
11	$1.18E^{-4}$	$3.70E^{-4}$	$3.93E^{-4}$
12	$1.23E^{-4}$	$9.30E^{-4}$	$2.06E^{-4}$
13	$4.62E^{-5}$	$2.94E^{-4}$	$1.53E^{-4}$
14	$1.74E^{-4}$	$8.11E^{-4}$	$2.77E^{-4}$
15	$2.01E^{-4}$	$7.54E^{-4}$	$3.09E^{-4}$
16	$1.69E^{-4}$	$2.98E^{-4}$	$2.44E^{-4}$
17	$1.90E^{-4}$	$5.25E^{-4}$	$2.55E^{-4}$
18	$9.20E^{-5}$	$2.40E^{-4}$	$1.16E^{-4}$
19	$2.74E^{-2}$	$1.10E^{-1}$	$9.24E^{-2}$
20	$7.26E^{-5}$	$1.35E^{-4}$	$1.16E^{-4}$
21	$7.97E^{-5}$	$2.79E^{-4}$	$1.99E^{-4}$
22	$1.93E^{-4}$	$2.35E^{-4}$	$1.87E^{-4}$
23	$1.30E^{-4}$	$4.25E^{-4}$	$2.43E^{-4}$
24	$1.05E^{-4}$	$8.90E^{-5}$	$1.93E^{-4}$
25	$1.29E^{-1}$	$2.44E^{-1}$	$9.82E^{-2}$
26	$1.65E^{-4}$	$5.02E^{-4}$	$1.97E^{-4}$
27	$5.78E^{-2}$	$3.11E^{-1}$	$2.00E^{-1}$
28	$7.17E^{-2}$	$2.93E^{-1}$	$2.41E^{-1}$
29	$7.57E^{-5}$	$1.12E^{-4}$	$1.55E^{-4}$
30	$1.60E^{-2}$	$8.09E^{-2}$	$8.50E^{-2}$

After normalization, EMG signals were full-rectified which means were taking the absolute value of the signal. The rectified signals were passed through a butterworth 5^{th} order low pass filter with cut off frequency of 10Hz. The sampling frequency of the

signal is 1000Hz. This process provided the linear envelope of signals. Furthermore, the filtered signals were amplitude-normalized to the peak MVIC EMG (nEMG) and then integrated in order to produce the *integrated EMG* (IEMG) values. The IEMG define as

$$IEMG = \int_{t_i}^{t_f} nEMG(t)dt \quad (3.1)$$

where n is the number of points in EMG grap. Also, t_i and t_f are initial and final time of recording respectively.

After normalization, the outliers were eliminated from the data set. This was estimated by plotting the normalization graph for each subject. If the subjects normalization graph were above 100% (the normalized graph should be between 0 to 1 or 0 -100%), the subject was eliminated from the data set. Figure 3.3, 3.4, 3.5 show the normalized graphs. The blue and red colors are related to CON and OR group respectively. By referring to Figure 3.3, there were two outliers in muscle 1 (subject 28, and 30) of OR group. In Figure 3.4 which is related to EMG signals for muscle 2, all EMG normalized graphs were in the range. However, in Figure 3.5, we had an outlier (subject 20) for CON group. Moreover, there were some subjects who had problems during the acquisitions. In other words, the EMG system had problems. Therefore, some channels were null (series of zeroes) and these subjects were removed from the data set (subject 4 and 26).

Figure 3.3: Normalized EMG Signals for CON (blue) and OR (red), Muscle 1

Figure 3.4: Normalized EMG Signals for CON (blue) and OR (red), Muscle 2

Figure 3.5: Normalized EMG Signals for CON (blue) and OR (red), Muscle 3

3.3 EMG Analysis Using Wavelet Transforms

Data analysis was performed using MATLAB programming language with the signal processing and Wavelet toolboxes (The Math Works, INC.). The EMG values were recorded from GMax, TFL, and RF muscles of the affected sides of the 30 subjects. There were 5 repetitions for every subject with sampling frequency of 1000Hz. The size of the samples in EMG data set was large, thus EMG signals were pre-processed by using the wavelet transform. As the size of EMG signals were reduced, unnecessary details were eliminated. EMG signals were recorded during squat cycles, thus each recorded signal was divided into three regions based on squat phases.

The analysis of the data file was started with converting it to .mat file and then removing any DC offset in order to be ready for the wavelet families' analysis. The

wavelet analysis was performed by a function called “analytical wavelet” or “mother wavelet”. There are different families or set of mother wavelets in Wavelet toolbox which differ in their mathematical principles named as Haar, Daubechies (db1 to db10), Symlets (sym2 to 8), Coiflets (coif1 to 5), Biorthogonal (bior1.1 to 6.8), Reverse biorthogonal (rbio1.1 to 6.8), Meyer (meyr), Discrete approximation of Meyer (dmey), Gaussian (gaus1 to 8), Mexican hat (mexh), and Morlet (morl). EMG signals were decomposed using DWT with various WFs. From the wavelet toolbox menu, we used discrete wavelet 1-D option which allowed us to decompose our EMG signals based on Haar, Daubechies (db1 to db10), Symlets (sym2 to 8), Coiflets (coif1 to 5), Biorthogonal (bior1.1 to 6.8), and discrete approximation of Meyer (dmey) mother wavelets. Moreover, MATLAB code was written for applying DWT to EMG signals. The WT decomposes a signal into several multi-resolution (levels) components based on basis functions or WFs. These WFs are achieved by dilation, contraction, and shifts of a unique function. Decomposition of the signal into basis of wavelet functions implies the computation of the inner products between the signal and the basis function, leading to a set of coefficients called *wavelet coefficients*.

3.3.1 Level of Decomposition

From Chapter 2 of this thesis, we have known that the wavelet transform is organized by different levels. The maximum level to apply the wavelet transform depends on how many data points contained in our data set, while there is a down-sampling by 2 operation from one level to the next level. In our analysis, we used 5 levels of decomposition.

3.3.2 Multi-Resolution Analysis

To compute multilevel wavelet decomposition, 38 different wavelet functions exerted at decomposition level 1 to 5. The wavelet coefficients from each wavelet function were used to calculate the energy of the sEMG signals for each subject in each phase.

3.3.3 Wavelet Selection Based on Energy Calculation

The wavelet energy was computed for approximation and detail coefficients. E_a is the percentage of energy corresponding to the approximation and E_d is the vector containing the percentage of energy corresponding to the details. E_d for each sEMG signal was collected after using 38 wavelet functions and the highest five energies were highlighted for each subject in three phases. Then, the highest repetition wavelet function was chosen as our wavelet function. This procedure is indicated in Figure 3.6.

Figure 3.6: Procedure of Selecting a WF

3.3.4 Wavelet Power Spectrum

Wavelet power spectrum is a way to determine the distribution of energy along the sEMG signal. In this procedure wavelet coefficients of the selected wavelet function was computed and the power spectrum was measured during 5 levels of decomposition. The distribution of power for each muscle during descending, stationary, and ascending phase for both CON and OR groups was determined and plotted. Figure 3.7 shows the block diagram for computing power and discriminating two groups based on their power spectrum.

Figure 3.7: Block Diagram for Computing Power Spectrum

Chapter 4

Analysis of Results

In this chapter, we will first describe how the EMG signals were analyzed. We introduce analysis methods and data used to achieve the methodology presented in chapter 3. Later, we explain the various procedures and present the results and analysis.

The algorithm developed in this study evaluated for its performance by discriminating the CON and OR group from one another. The comparisons were made by three different procedures including:

1. Computing IEMG values
2. Selecting a wavelet function
3. Computing the wavelet power spectrum

4.1 Data Selection

In this study, the acquisition of the EMG signal achieved from a total of 30 subjects, which consist of 16 CONs and 14 ORs, to perform a squat activity. The “Dataset.mat” file contained the data for all subjects. Within a subject there were various fields such as; MVIC, Trial, Group, Gender, Height, Weight.

- **Maximum Voluntary Isometric Contraction (MVIC):** The maximum value of tension a muscle can generate and hold was collected and referred to GMax, TFL, and RF of the affected side of the subject.
- **Trial:** The trial field contained 5 columns (structure array of 1x5) as there were 5 repetitions for every subject. Each column of this trial contained the AnChEMG (analog channel EMG) and Events fields. The AnChEMG was a matrix nx3, where n was the number of frames (duration of the acquisition with sampling frequency of 1000 Hz) and the 3 was the number of muscles (GMax, TFL, RF which are Muscle1, Muscle2, and Muscle3 respectively). Moreover, the events field included a 4 number array corresponding to 1-start of descending phase of squat, 2-end of descending phase, 3-start of ascending phase, 4-end of ascending phase respectively. Figure 3.2 shows these events.
- **Group, gender, height, and weight:** In chapter 3, Table 3.1 illustrates participant characteristics.

EMG data were recorded from GMax, TFL, and RF muscles during dynamic contraction for descending, stationary, and ascending phases. After removing the DC offset from sEMG signals and normalizing them some of the sEMG graphs were out

of range of normalization (0-1). Thus, these subjects were considered as outliers.

EMG signals during squat cycles were normalized by dividing the EMG signal of each muscle by the MVIC related to that specific muscle for each subject. Then, EMG signals were full-rectified and passed through a butterworth low pass filter (5^{th} order) with the 10Hz cutoff frequency. The result of this process was the linear envelopes of signals. The filtered signals were integrated and IEMG values were computed for both CON and OR groups in order to distinguish between them. The IEMG graphs for Gmax, TFL, and RF muscles (muscle 1, 2, and 3) are plotted in Figure 4.1, 4.2, 4.3, respectively. Moreover, IEMG values for each muscle are provided in appendix A.

Figure 4.1: Integrated EMG Graphs for CON (blue) and OR (red), Muscle 1

Figure 4.2: Integrated EMG Graphs for CON (blue) and OR (red), Muscle 2

Figure 4.3: Integrated EMG Graphs for CON (blue) and OR (red), Muscle 3

Then, IEMGs were time normalized by dividing them to the length of signals. The IEMG and time normalized values for CON and OR groups are provided in tables

Figure 4.4: Time Normalized IEMG for Muscle 1

Figure 4.5: Time Normalized IEMG for Muscle 2

Figure 4.6: Time Normalized IEMG for Muscle 3

The results obtained show that the two groups are not separable based on their IEMG value and even time normalized IEMG graphs. Thus, time-frequency methods will be used in order to convert the signal from time domain to frequency domain.

4.2 Wavelet Transforms

The acquired EMG data were analyzed in MATLAB. Various wavelets were utilized to analyze raw sEMG signals. The DWT was applied to EMG signals which collected from GMax, TFL, and RF muscles (muscle 1, 2, and 3 respectively). The mother wavelets in this study include Haar, Daubechies 1 to 10, Symlets 2 to 8, Coiflets 1 to 5, Biorthogonal 1.1 to 6.8, and discrete approximation of Meyer. As the sEMG signals are composed of the superposition of the activity of individual MUs, each mother

wavelet available within Wavelet Toolbox was used to decompose sEMG signals into their constituent components.

4.2.1 Selecting a Wavelet Function

EMG signals which were collected from three muscles were analyzed by 38 wavelet functions with 5 levels of decomposition for three phases of dynamic contraction during squat task. The wavelets energies were computed using *wenergy* function in MATLAB. The 5 wavelet functions that represented the highest amount of energy for each subject were highlighted. A sample of energy after EMG decomposition with 38 various wavelet functions is illustrated in Table 4.1 (CON) and 4.2 (OR) for muscle 3 during descending phase.

Table 4.1: Energy of Muscle3 During Descending Phase for One CON Subject

Wavelet Function	Level 1	Level 2	Level 3	Level 4	Level 5
Haar	15.120	27.529	34.690	16.591	4.856
db2	10.220	27.896	36.518	20.949	3.197
db3	9.785	23.660	40.100	17.346	5.518
db4	10.502	21.962	41.368	21.702	3.459
db5	10.049	22.521	40.100	19.809	4.189
db6	9.176	21.826	41.574	18.809	5.300
db7	8.046	20.627	42.055	20.300	2.800
db8	7.761	22.592	41.346	19.390	3.732
db9	7.774	22.194	39.522	18.620	4.799
db10	8.444	20.238	43.060	19.488	2.459
sym2	10.220	27.896	36.518	20.949	3.197
sym3	9.785	23.660	40.100	17.346	5.518
sym4	8.891	21.050	38.883	16.105	4.991
sym5	7.830	21.696	38.846	19.735	2.744
sym6	8.463	22.090	38.997	16.688	5.269
sym7	8.564	21.338	38.200	20.650	2.364
sym8	8.587	20.763	42.896	19.311	3.631
coif1	11.569	23.149	36.864	16.557	5.047
coif2	9.166	20.632	38.418	17.805	5.534
coif3	8.739	19.966	40.307	19.535	3.033
coif4	8.612	19.975	43.066	20.828	2.865
coif5	8.436	19.785	42.044	24.403	4.077
bior1.1	15.120	27.529	34.690	16.591	4.856
bior1.3	12.044	26.592	34.413	16.518	2.682
bior1.5	11.064	24.338	35.020	18.426	2.460
bior2.2	4.824	14.425	38.522	23.018	9.213
bior2.4	4.767	15.283	39.407	21.715	8.427
bior2.6	4.633	14.8250	43.120	22.726	7.580
bior2.8	4.567	15.491	40.996	29.308	5.7048
bior3.1	0.865	4.250	20.502	19.406	18.944
bior3.3	1.733	8.826	36.100	30.636	7.914
bior3.5	1.818	8.897	43.999	32.089	6.204
bior3.7	1.937	9.931	43.355	32.706	7.727
bior3.9	1.847	9.214	46.372	31.282	9.722
bior4.4	8.722	20.148	38.495	17.991	5.734
bior5.5	14.124	24.915	34.242	13.928	4.516
bior6.8	7.673	19.437	39.891	24.474	4.434
dmey	7.530	18.164	43.968	24.822	3.789

Table 4.2: Energy of Muscle3 During Descending Phase for One OR Subject

Wavelet Function	Level 1	Level 2	Level 3	Level 4	Level 5
Haar	15.441	22.152	28.738	31.408	1.585
db2	12.192	19.143	29.079	35.957	1.931
db3	11.325	17.618	28.551	37.383	2.065
db4	11.032	16.790	26.697	38.895	1.652
db5	11.040	16.697	27.399	37.952	1.914
db6	10.902	16.651	25.619	40.017	2.118
db7	10.740	17.213	26.873	40.481	1.727
db8	10.400	17.066	24.564	42.755	2.060
db9	10.331	16.843	25.708	40.969	2.656
db10	10.358	16.712	23.525	42.447	2.561
sym2	12.192	19.143	29.079	35.957	1.931
sym3	11.325	17.618	28.551	37.383	2.065
sym4	11.343	16.982	28.263	37.667	1.878
sym5	10.568	17.073	26.595	37.263	1.627
sym6	10.480	16.350	24.787	38.049	1.668
sym7	10.515	16.832	26.468	38.674	1.354
sym8	10.620	17.153	24.540	40.232	1.534
coif1	12.308	18.091	29.336	34.931	2.393
coif2	11.021	16.771	26.075	37.916	1.721
coif3	10.708	16.753	26.577	39.663	1.404
coif4	10.492	16.805	23.920	42.391	2.870
coif5	10.575	16.901	25.096	43.061	2.884
bior1.1	15.441	22.152	28.738	31.408	1.585
bior1.3	12.607	20.070	27.734	35.216	1.347
bior1.5	11.483	19.312	26.912	35.102	1.051
bior2.2	4.751	13.865	14.825	59.455	3.717
bior2.4	4.311	12.774	13.690	59.857	2.780
bior2.6	4.174	12.822	12.633	61.436	2.501
bior2.8	4.184	13.144	13.744	63.158	1.925
bior3.1	0.924	6.423	5.133	59.544	3.052
bior3.3	1.432	9.331	5.853	75.889	3.281
bior3.5	1.441	8.949	5.844	75.392	2.656
bior3.7	1.447	8.855	6.117	76.127	3.356
bior3.9	1.389	8.387	5.274	81.126	2.814
bior4.4	10.175	19.480	18.685	42.464	2.277
bior5.5	19.749	24.367	21.770	25.625	1.529
bior6.8	9.084	17.317	19.540	47.831	1.650
dmey	8.963	14.621	20.305	50.309	4.627

The highest five energies were indicated in red in Table 4.2. The same scenario was repeated for all subjects with analyzing EMG signals from all three muscles for each descending, stationary, and ascending phase separately. The highest five energies occurred in various levels for different subjects and muscles. The five WFs that indicated the highest percentage of energy were selected for each subject. Table 4.3 and 4.4 show the five selected WFs for one CON and OR subject.

Table 4.3: Five Wavelet Functions With Highest Energy for Muscle 3 During Descending Phase of One CON Subject

Wavelet Function	Level 1	Level 2	Level 3	Level 4	Level 5
bior2.6	4.633	14.825	43.120	22.726	7.580
bior3.5	1.818	8.897	43.999	32.089	6.204
bior3.7	1.937	9.931	43.355	32.706	7.727
bior3.9	1.847	9.214	46.372	31.282	9.722
dmey	7.530	18.164	43.968	24.822	3.789

Table 4.4: Five Wavelet Functions With Highest Energy for Muscle 3 During Descending Phase of One OR Subject

Wavelet Function	Level 1	Level 2	Level 3	Level 4	Level 5
bior2.8	4.184	13.144	13.743	63.158	1.925
bior3.3	1.432	9.331	5.853	75.889	3.281
bior3.5	1.441	8.949	5.844	75.392	2.656
bior3.7	1.447	8.855	6.117	76.127	3.356
bior3.9	1.389	8.387	5.274	81.126	2.814

The total number of repetition of wavelet functions between CON and OR group during descending, stationary, and ascending phases were computed for each muscle separately. Based on our observation (Tables 4.5 - 4.10) there is not a single wavelet function that gives the best contrast between all subjects.

Table 4.5: Selection of a WF With Highest Repetition of Energy for Muscle 1-CON

Wavelet Function	Descending	Stationary	Ascending	Total
Haar	1	3	0	4
db2	0	0	0	0
db3	1	1	0	2
db4	1	2	3	6
db5	1	1	4	6
db6	2	4	1	7
db7	0	2	3	5
db8	3	2	5	10
db9	1	2	3	6
db10	2	2	6	10
sym2	1	1	0	2
sym3	1	1	0	2
sym4	1	1	0	2
sym5	3	0	2	5
sym6	0	1	2	3
sym7	0	1	3	4
sym8	1	0	3	4
coif1	0	0	0	0
coif2	0	0	1	1
coif3	0	3	1	4
coif4	1	0	2	3
coif5	3	3	3	9
bior1.1	1	3	0	4
bior1.3	1	0	0	1
bior1.5	1	0	0	1
bior2.2	1	0	1	2
bior2.4	2	2	2	6
bior2.6	2	2	4	8
bior2.8	5	5	6	16
bior3.1	0	1	0	1
bior3.3	7	6	0	13
bior3.5	6	5	3	14
bior3.7	7	6	4	17
bior3.9	12	6	7	25
bior4.4	1	1	1	3
bior5.5	4	1	0	5
bior6.8	1	4	3	8
dmey	4	9	7	20

Table 4.6: Selection of a WF With Highest Repetition of Energy for Muscle 1-OR

Wavelet Function	Descending	Stationary	Ascending	Total
Haar	1	4	0	5
db2	0	0	0	0
db3	1	1	1	3
db4	1	3	3	7
db5	3	1	1	5
db6	1	0	4	5
db7	0	2	4	6
db8	3	3	4	10
db9	2	2	3	7
db10	3	2	3	8
sym2	0	1	0	1
sym3	1	1	1	3
sym4	2	1	1	4
sym5	2	0	2	4
sym6	1	0	1	2
sym7	0	1	3	4
sym8	1	0	2	3
coif1	1	1	0	2
coif2	0	0	1	1
coif3	1	0	2	3
coif4	2	1	3	6
coif5	2	2	2	6
bior1.1	1	4	0	5
bior1.3	0	0	0	0
bior1.5	0	0	0	0
bior2.2	2	1	1	4
bior2.4	1	0	1	2
bior2.6	0	0	1	1
bior2.8	0	1	2	3
bior3.1	1	0	0	1
bior3.3	4	2	0	6
bior3.5	6	3	1	10
bior3.7	6	6	4	16
bior3.9	4	6	4	14
bior4.4	0	1	0	1
bior5.5	3	0	0	3
bior6.8	0	1	1	2
dmey	3	7	5	15

Table 4.7: Selection of a WF With Highest Repetition of Energy for Muscle 2-CON

Wavelet Function	Descending	Stationary	Ascending	Total
Haar	0	3	0	3
db2	0	0	1	1
db3	1	2	3	6
db4	3	0	2	5
db5	1	3	3	7
db6	1	1	1	3
db7	5	1	4	10
db8	2	1	5	8
db9	6	1	4	11
db10	2	2	0	4
sym2	2	3	2	7
sym3	1	2	3	6
sym4	2	1	3	6
sym5	0	1	3	4
sym6	1	1	0	2
sym7	2	1	2	5
sym8	1	1	2	4
coif1	0	1	1	2
coif2	0	1	0	1
coif3	3	1	3	7
coif4	0	0	3	3
coif5	6	6	4	16
bior1.1	0	3	0	3
bior1.3	2	0	0	2
bior1.5	0	0	0	0
bior2.2	1	2	2	5
bior2.4	2	1	1	4
bior2.6	2	1	0	3
bior2.8	3	4	5	12
bior3.1	0	0	0	0
bior3.3	3	5	3	11
bior3.5	6	6	4	16
bior3.7	7	3	4	14
bior3.9	8	8	4	20
bior4.4	0	0	0	0
bior5.5	0	0	0	0
bior6.8	1	1	4	6
dmey	4	10	4	18

Table 4.8: Selection of a WF With Highest Repetition of Energy for Muscle 2-OR

Wavelet Function	Descending	Stationary	Ascending	Total
Haar	0	2	0	2
db2	0	0	0	0
db3	0	2	1	3
db4	1	3	1	5
db5	3	1	2	6
db6	3	1	2	6
db7	1	2	0	3
db8	3	2	3	8
db9	2	2	2	6
db10	1	1	1	3
sym2	1	1	0	2
sym3	0	2	1	3
sym4	1	1	2	4
sym5	1	1	2	4
sym6	0	0	0	0
sym7	1	1	2	4
sym8	2	0	1	3
coif1	0	0	1	1
coif2	0	0	0	0
coif3	0	2	1	3
coif4	1	0	1	2
coif5	0	5	3	8
bior1.1	0	2	0	2
bior1.3	0	0	0	0
bior1.5	0	1	0	1
bior2.2	2	0	3	5
bior2.4	3	1	2	6
bior2.6	1	0	2	3
bior2.8	5	6	5	16
bior3.1	0	0	0	0
bior3.3	1	2	1	4
bior3.5	7	2	6	15
bior3.7	8	3	6	17
bior3.9	9	7	9	25
bior4.4	0	0	0	0
bior5.5	0	0	1	1
bior6.8	3	3	3	9
dmey	4	8	2	14

Table 4.9: Selection of a WF With Highest Repetition of Energy for Muscle 3-CON

Wavelet Function	Descending	Stationary	Ascending	Total
Haar	0	4	0	4
db2	0	2	0	2
db3	1	1	0	2
db4	2	2	2	6
db5	1	0	1	2
db6	1	1	1	3
db7	5	1	2	8
db8	4	0	4	8
db9	3	2	2	7
db10	7	2	3	12
sym2	0	6	1	7
sym3	1	1	0	2
sym4	1	0	0	1
sym5	0	1	1	2
sym6	2	1	0	3
sym7	2	1	3	6
sym8	2	3	6	11
coif1	1	0	0	1
coif2	3	0	0	3
coif3	0	1	3	4
coif4	4	3	5	12
coif5	2	5	2	9
bior1.1	0	4	0	4
bior1.3	0	1	2	3
bior1.5	0	1	0	1
bior2.2	1	0	1	2
bior2.4	3	0	2	5
bior2.6	4	1	0	5
bior2.8	2	2	6	10
bior3.1	0	0	0	0
bior3.3	0	2	0	2
bior3.5	8	5	2	15
bior3.7	8	3	11	22
bior3.9	7	8	13	28
bior4.4	2	0	0	2
bior5.5	0	1	0	1
bior6.8	1	0	2	3
dmey	2	11	4	17

Table 4.10: Selection of a WF With Highest Repetition of Energy for Muscle 3-OR

Wavelet Function	Descending	Stationary	Ascending	Total
Haar	0	4	0	4
db2	0	0	0	0
db3	0	2	0	2
db4	0	1	0	1
db5	0	2	0	2
db6	3	2	1	6
db7	2	2	1	5
db8	1	1	2	4
db9	3	2	3	8
db10	2	1	1	4
sym2	0	0	0	0
sym3	0	2	0	2
sym4	0	0	1	1
sym5	3	0	1	4
sym6	1	0	2	3
sym7	2	1	2	5
sym8	2	2	3	7
coif1	0	0	1	1
coif2	0	0	1	1
coif3	0	2	1	3
coif4	3	1	2	6
coif5	0	5	2	7
bior1.1	0	4	0	4
bior1.3	0	0	0	0
bior1.5	0	0	0	0
bior2.2	0	1	3	4
bior2.4	0	1	2	3
bior2.6	3	1	3	7
bior2.8	7	2	5	14
bior3.1	0	1	0	1
bior3.3	2	0	3	5
bior3.5	7	2	8	17
bior3.7	6	6	6	18
bior3.9	7	10	6	23
bior4.4	2	1	0	3
bior5.5	2	1	0	3
bior6.8	3	2	2	7
dmey	3	5	3	11

Bior3.9 wavelet function indicated the highest number of repetitions between subjects for each muscle during three phases except for muscle 1 of OR group which Bior3.7 worked best (Table 4.6). As the difference between Bior3.7 and Bior3.9 was not significant in muscle 1 of OR group, Bior3.9 wavelet function was used for further analyses.

4.2.2 Principal Component Analysis

An energy matrix was created from Bior3.9 and the *Principal Component Analysis* (PCA) method was applied on it. PCA is a data analysis method which involves a mathematical procedure that converts a number of correlated variables into a number of uncorrelated variables called *principal components* (PCs). The goal of using PCA is to reduce the dimensionality of the data set to identify new meaningful underlying variables. The PCA is a $n \times p$ matrix that has n observations and p variables. The PCA function was used for a 2D matrix and applied to the Bior3.9 energy matrix in order to discriminate two groups of subjects. This function returns a $p \times p$ *matrix of coefficients* that each column was related to one of our PCs (column one for PC_1 and column two for PC_2). Furthermore, the PCA function prepared a *SCORE* matrix which represents the energy matrix in the PC space. Each column of SCORE corresponds to one PC. Plotting PC_1 versus PC_2 did not assess us to discriminate two groups.

4.2.3 Bior3.9 Energy and Weight

Bior3.9 energy for descending, stationary, and ascending phases was plotted for each muscle versus the weight of each subjects. Figures 4.7, 4.8, 4.9 represent the energy versus weight for muscle 1 during squat cycles. Figures 4.10, 4.11, 4.12 show for muscle 2 and Figures 4.13, 4.14, 4.15 indicate the graphs for muscle 3. By referring to these graphs the two groups were not distinguishable based on their energy (both groups indicated almost the same amount of energies). Furthermore, the weight of subjects was not a good parameter to separate them.

Figure 4.7: Bior3.9 Energy versus Weight for Muscle 1 in Descending Phase

Figure 4.8: Bior3.9 Energy versus Weight for Muscle 1 in Stationary Phase

Figure 4.9: Bior3.9 Energy versus Weight for Muscle 1 in Ascending Phase

Figure 4.10: Bior3.9 Energy versus Weight for Muscle 2 in Descending Phase

Figure 4.11: Bior3.9 Energy versus Weight for Muscle 2 in Stationary Phase

Figure 4.12: Bior3.9 Energy versus Weight for Muscle 2 in Ascending Phase

Figure 4.13: Bior3.9 Energy versus Weight for Muscle 3 in Descending Phase

Figure 4.14: Bior3.9 Energy versus Weight for Muscle 3 in Stationary Phase

Figure 4.15: Bior3.9 Energy versus Weight for Muscle 3 in Ascending Phase

4.2.4 Average Energy

The highest amount of energy for each subject during descending, stationary, and ascending phases was computed (appendix A). Then, the average energy which is the summation of energy from three phases divided by 3 (squat phases) was calculated and plotted in Figure 4.16.

Figure 4.16: Average Energy for Muscle 1, 2, and 3

4.2.5 Wavelet Power Spectrum

The WT converts the data array, which is stored from the EMG recorded signal, into a series of wavelet coefficients. Each of these coefficients represents the amplitude of the wavelet function at a specific location in the array. The best way to specify the distribution of energy within the data is to compute the wavelet power. The power, which is the squared absolute value of the wavelet coefficients, calculated as

$$WP = |WC_i|^2 \quad (4.1)$$

where WC is wavelet coefficients and i is the index for it.

Therefore, we compute the wavelet power spectrum for each muscle during descending, stationary, and ascending phases by using Bior3.9 WF. Tables 4.11, 4.12, and 4.13 illustrate a sample of calculated wavelet Bior3.9 power after 5 decomposition levels for one CON subject.

Table 4.11: Example of Wavelet Power Spectrum Calculations for Muscle 1 of One CON Subject

	Level 1	Level 2	Level 3	Level 4	Level 5
Descending (D)	5.887	7.406	9.834	12.364	12.442
Stationary (S)	0.669	1.131	1.449	1.899	2.529
Ascending (A)	42.010	59.763	104.155	111.192	112.685

Table 4.12: Example of Wavelet Power Spectrum Calculations for Muscle 2 of One CON Subject

	Level 1	Level 2	Level 3	Level 4	Level 5
Descending (D)	20.990	26.399	35.836	46.450	39.715
Stationary (S)	0.025	0.043	0.058	0.078	0.104
Ascending (A)	2.244	2.593	3.320	4.911	3.860

Table 4.13: Example of Wavelet Power Spectrum Calculations for Muscle 3 of One CON Subject

	Level 1	Level 2	Level 3	Level 4	Level 5
Descending (D)	326.453	534.807	644.757	637.505	632.421
Stationary (S)	48.383	95.583	112.166	117.314	129.691
Ascending (A)	91.764	155.638	167.959	166.553	168.692

Furthermore, Tables 4.14, 4.15, and 4.16 show a sample of power calculation for one OR subject (refer to the wavelet power spectrum section in appendix A for power calculation for other subjects).

Table 4.14: Example of Wavelet Power Spectrum Calculations for Muscle 1 of One OR Subject

	Level 1	Level 2	Level 3	Level 4	Level 5
Descending (D)	4.897	6.234	7.728	8.162	8.667
Stationary (S)	1.083	1.525	3.229	4.137	4.935
Ascending (A)	220.683	282.050	495.946	604.871	578.224

Table 4.15: Example of Wavelet Power Spectrum Calculations for Muscle 2 of one OR Subject

	Level 1	Level 2	Level 3	Level 4	Level 5
Descending (D)	10.424	15.486	19.268	20.263	22.215
Stationary (S)	3.239	5.794	6.606	8.119	8.875
Ascending (A)	43.230	60.027	73.495	73.003	72.547

Table 4.16: Example of Wavelet Power Spectrum Calculations for Muscle 3 of One OR Subject

	Level 1	Level 2	Level 3	Level 4	Level 5
Descending (D)	209.650	356.795	366.922	351.304	350.055
Stationary (S)	65.453	135.278	210.988	261.701	292.567
Ascending (A)	400.546	605.973	723.068	818.077	823.966

Then the power after 5 decomposition levels was plotted separately for OR and CON subjects during squat phases. Figures 4.17- 4.19 represent a sample of the wavelet power values for muscle 1, 2, and 3 of a CON subject.

Figure 4.17: Example of Wavelet Power for Muscle 1 of One CON Subject

Figure 4.18: Example of Wavelet Power for Muscle 2 of One CON Subject

Figure 4.19: Example of Wavelet Power for Muscle 3 of One CON Subject

Figure 4.20: Example of Wavelet Power for Muscle 1 of One OR Subject

Figure 4.21: Example of Wavelet Power for Muscle 2 of One OR Subject

Figure 4.22: Example of Wavelet Power for Muscle 3 of One OR Subject

Additionally, the above scenario was repeated for all subjects from both groups. The subjects were categorized based on calculated power of each phase in Table 4.17. OR and CON groups were divided into three categories based on the squat phases (Table 4.17). All 16 subjects in the CON group used their muscle 1 in the ascending phase whereas, most of them used muscle 2 and muscle 3 in their descending phase. In OR group, muscle 1 was used in ascending the same as CON group. However, muscle 2 was used in ascending and muscle 3 in both descending and ascending phases.

Table 4.17: Muscles used by CON and OR During Squat Cycle

	Descending	Stationary	Ascending	Total
CON				
M_1	0	0	16	16
M_2	10	2	4	16
M_3	14	2	0	16
OR				
M_1	2	0	10	12
M_2	4	0	8	12
M_3	5	2	5	12

Moreover, after calculating the power of the DWT coefficients at various levels, the power was then compared for the sEMG for OR and CON group of three muscles (GMax, TFL, RF). Figures 4.23, 4.24, 4.25 show the results of each muscle for both groups and Figures 4.26, 4.27 represent the same result but in a different orientation, this time we consider the power of each group separately.

Figure 4.23: Power of Muscle 1 for CON and OR during squat cycles

Figure 4.24: Power of Muscle 2 for CON and OR during squat cycles

Figure 4.25: Power of Muscle 3 for CON and OR during squat cycles

Figure 4.26: Muscles Power for CON Group

Figure 4.27: Muscles Power for OR Group

As indicated in above graphs, subjects from both groups used higher power in descending and ascending phases. In order to indicate whether there is a significant difference between these two groups in using their muscles during ascending (A) and descending (D) phases, the actual ratio A/D for CON and OR were computed. Therefore, we had a continuous number instead of a discrete number (the ratio) that gave more information on how much each muscle was more active during one phase compare to another phase. Tables 4.18 and 4.19 illustrate the ratio of ascending over descending phases for one CON and OR subject respectively (refer to appendix B for all other subjects).

Table 4.18: Ratio A/D Phase for One CON Subject

	Level 1	Level 2	Level 3	Level 4	Level 5
M_1	7.136	8.070	10.591	8.993	9.057
M_2	0.107	0.098	0.093	0.106	0.097
M_3	0.281	0.291	0.260	0.261	0.267

Table 4.19: Ratio A/D Phase for One OR Subject

	Level 1	Level 2	Level 3	Level 4	Level 5
M_1	45.068	45.246	64.179	74.109	66.716
M_2	4.147	3.876	3.814	3.603	3.266
M_3	1.911	1.698	1.971	2.329	2.354

By calculating the ratio we are still capable of seeing which phase was the most active; however we are also able to see the extend of activity. Therefore, we calculated the ratio of A/D for every subject in CON and OR groups and then the average was calculated. The average for each muscle is provided in Table 4.20 with the standard deviation for each group.

Table 4.20: Average Ratio With Standard Deviation Values for Each Muscle in CON and OR Groups

	CON	OR
Muscle 1 (Gmax)	13.380 ± 1.902	11.319 ± 1.921
Muscle 2 (TFL)	1.330 ± 0.150	1.829 ± 0.205
Muscle 3 (RF)	0.613 ± 0.090	1.975 ± 0.260

The muscles power is plotted in Figure 4.28 for CON and OR group. In CON group muscle 1 and 2 were active in ascending phase whereas muscle 3 was active in descending phase. Moreover, in OR group all three muscles were active in the ascending phase.

Figure 4.28: Average Ratio Muscle Power for CON and OR

4.2.6 Algorithm

In general, the described algorithm can be summarized as follow:

The raw EMG signals are collected from a participant for GMax, TFL, RF muscles during descending, stationary, and ascending phases of squat task. Then, the collected EMG signals are normalized. Bior3.9 wavelet function is applied to normalized EMG signals and the wavelet coefficients will be computed. Based on wavelet coefficients the wavelet power spectrum is calculated. In addition, the ratio power which is the ratio of ascending power over descending power is computed in order to identify whether the subject has FAI or not. If the ratio value for RF muscle is less than zero, it means the participant used his/her RF muscle in descending phase and he/she belongs to

CON group. Whereas, if the ratio value is greater than zero, it means he/she used his/her muscle in ascending phase and the subject belongs to FAI group.

4.3 Statistical Analysis

In this study an independent samples t-test was used to check if the two means (averages) from CON and OR groups are reliably different from one another. Each t-value has a p-value that is the probability that the pattern of data in the sample could be produced by random data. The 2-tail t-test was applied to check the activities of muscles for CON and OR groups. Table 4.21 illustrates no significant difference was found for muscle 1 (GMax) and muscle 2 (TFL). Whereas muscle 3 (RF) almost shows a significant difference between CON and OR groups ($p=0.0670$) although the threshold ($p=0.05$) was not reached. This can be due to the fact that the sample size in this study was small and we require more samples for more reliable results.

Table 4.21: P-value for GMax, TFL, and RF Muscle

	P-value
Muscle 1 (Gmax)	0.7477
Muscle 2 (TFL)	0.4997
Muscle 3 (RF)	0.0670

4.4 Discussion

Spectral properties of EMG signals have been defined by their power spectra. The shape of the power spectrum can be changed when the EMG signals are generated from different types of MU [72–74].

This study has indicated the wavelet transform method can be used to quantify features of the muscle activity for dynamic contraction. The fundamental properties of EMG spectra are conserved across dynamic contraction, therefore the WT will be a useful tool for studying EMG signals. The wavelet power spectrum of OR and CON groups was analyzed for GMax, TFL, and RF muscles in hip area by using Bior3.9 wavelet function in order to discriminate the two groups. The power was calculated for each muscle and an independent sample t-test was used to check the activity of three muscles in hip area to discriminate an OR patient from a healthy person. The p-value for GMax, TFL, and RF muscles is 0.7477, 0.4997, and 0.0670 respectively for 2-tail test. Therefore, RF muscle is almost statistically significant although the threshold ($p=0.05$) was not reached due to small sample size. As a result, RF muscle is more active in ascending than descending phase for OR people, whereas it is more active in descending phase for CON people.

Muscle contraction is produced by a sequence of electrical and chemical events which start with an action potential which is created at the neuromuscular junction. Individual muscle fibers are classified into three primary muscle fiber types named *type I*, *type IIA*, and *type IIB* based on their contractile and metabolic properties. Type I is referred to slow twitch oxidative, type IIA is fast twitch oxidative and type IIB is fast twitch glycolytic [75]. These three types of muscle fibers have very different functional characteristics. Type I fiber is characterized by low force, power, speed production and high endurance. Type IIB has high force, power, speed production and low endurance, while type IIA indicates feature between the two other types. The MU consists of a single motoneuron and the group of muscle fiber it innervates. All muscle fibers in a single MU contain the same muscle fiber type. Three types of

MUs (slow, fast fatigue-resistant, and fast fatigable) are categorized on the basis of their twitch speed and fatigability. The slow twitch MU is small and can produce less force compare to fast twitch MU. Type I muscle MUs contract slower, and they reach to peak power slower and highly resistant to fatigue compare to type II fast twitch MUs. Type IIA and IIB are capable of the same amount of peak force, however type IIA fibers take longer to reach their peak power compare to type IIB. Therefore, the total peak power by type IIB is higher than type IIA. In other words, type I has low intensity, lower frequency, and low power compare to type II.

The average ratio (ascending over descending phase) power for GMax, TFL, and RF muscles, as indicated in Table 4.20, presents the power of RF muscle is higher in OR group than CON group. The faster motor units generate higher frequencies in their power spectra [76]. Thus, the larger numbers of MUs are recruitment in RF muscle for OR than CON. Therefore, type II (fast twitch) MUs are active in OR group, while in CON group type I (slow twitch) MUs are used.

Chapter 5

Conclusions and Future Work

The algorithm developed in this study aimed to automatically discriminate CON and OR groups based on sEMG recorded from three hip muscles (GMax, TFL, and RF) during dynamic contraction. The program was capable of identifying OR from healthy people by analyzing the activity of hip muscles.

The novel method developed in this study was used to analyze EMG signals recorded from GMax, TFL, and RF muscles for 16 CON and 14 OR subjects during squat cycles. EMG signals are non-stationary signals, therefore time-frequency analysis based on wavelet transform methods were used. In this study the DWT was selected and various wavelet functions from this WT method were applied to EMG signals from three muscles in order to select the best possible energy localization in the time-frequency plane. This analysis showed the Bior3.9 wavelet function provided higher amount of energy for most of our subjects. By selecting Bior3.9 the wavelet power spectrum was computed for CON and OR during 5 levels of decomposition. The result indicated the RF muscle (muscle 3) is more active in ascending phase than

descending phase for OR, while it is more active in descending phase for CON.

During dynamic contraction there is a progressive recruitment of faster MUs in OR group during ascending phase. EMG activity at higher frequencies correlated with higher contractile force, and with the progressively faster types of MU which can be assumed to be recruited. Thus, during dynamic contraction the higher wavelet power in RF muscle of OR group demonstrates that faster MUs were active, while lower power in CON group related to the fact that slower MUs were active.

This research work showed that the proposed algorithm is able to find a good solution for pre-screening problem. Nevertheless, some more improvements could be achieved. In this algorithm, only the three muscles of hip area were considered, this might be different if we consider all the muscles in the hip area. Another limitation is that the physical activity and age parameters of subjects were not available. Therefore, research should be conducted in a wider range, parameters like physical activity, age, and gender could be considered.

Some future work from this thesis may consist of considering a larger sample size for more accurate and reliable values. Ultimate goal can be developing a software application which can assist doctors and physicians to diagnose FAI faster and easier.

Appendix A

In this appendix, we present numerical results for this study including all tables for different steps.

IEMG and Time Normalized EMG

The IEMG and time normalized values for CON and OR groups are presented in Table A.1, A.2, and A.3 for muscle 1, 2, and 3 respectively.

Table A.1: IEMG and Time Normalized Values for Muscle 1 Without Outliers

Subject	Integrated EMG	Length of Signal	Time Normalization
CON			
1	377.219	5180	0.073
2	478.673	4415	0.108
5	298.995	4745	0.063
6	452.587	8345	0.054
7	360.346	3870	0.093
10	459.621	6275	0.073
11	379.996	5035	0.075
12	447.927	5575	0.080
15	168.690	4595	0.037
17	255.802	4730	0.054
19	1585.495	7500	0.211
20	525.173	4070	0.129
22	174.778	4640	0.038
23	309.871	3050	0.102
24	238.147	5065	0.047
25	305.486	5150	0.060
OR			
3	251.270	4040	0.062
8	470.763	6370	0.074
9	221.722	6890	0.032
13	521.575	4505	0.116
14	592.230	10580	0.056
16	474.705	6460	0.073
18	418.132	6575	0.064
21	531.754	7365	0.072
27	2454.064	6100	0.402
29	484.184	3365	0.144

Table A.2: IEMG and Time Normalized Values for Muscle 2 Without Outliers

Subject	Integrated EMG	Length of Signal	Time Normalization
CON			
1	403.563	5180	0.078
2	842.446	4415	0.191
5	905.356	4745	0.191
6	277.228	8345	0.033
7	443.272	3870	0.115
10	424.274	6275	0.068
11	114.021	5035	0.023
12	59.486	5575	0.011
15	90.380	4595	0.020
17	207.423	4730	0.044
19	997.866	7500	0.133
20	282.975	4070	0.070
22	330.157	4640	0.071
23	104.439	3050	0.034
24	771.032	5065	0.152
25	230.499	5150	0.045
OR			
3	141.236	4040	0.035
8	1545.059	6370	0.243
9	1142.234	6890	0.166
13	185.388	4505	0.041
14	202.193	10580	0.019
16	230.616	6460	0.036
18	371.761	6575	0.057
21	399.293	7365	0.054
27	654.696	6100	0.107
28	163.525	3095	0.053
29	286.109	3365	0.085
30	531.612	4950	0.107

Table A.3: IEMG and Time Normalized Values for Muscle 3 Without Outliers

Subject	Integrated EMG	Length of Signal	Time Normalization
CON			
1	641.209	5180	0.124
2	343.034	4415	0.078
5	698.830	4745	0.147
6	1835.176	8345	0.220
7	1225.814	3870	0.317
10	980.394	6275	0.156
11	680.335	5035	0.135
12	538.071	5575	0.097
15	554.491	4595	0.121
17	948.499	4730	0.201
19	1743.782	7500	0.233
22	1007.532	4640	0.217
23	467.060	3050	0.153
24	549.610	5065	0.109
25	1366.655	5150	0.265
OR			
3	848.363	4040	0.210
8	1026.715	6370	0.161
9	617.380	6890	0.090
13	752.812	4505	0.167
14	1588.370	10580	0.150
16	657.576	6460	0.102
18	1369.372	6575	0.208
21	1246.705	7365	0.169
27	135.664	6100	0.022
28	85.839	3095	0.028
29	787.682	3365	0.234
30	288.251	4950	0.0583

Average Energy

The highest amount of energy for each subject during squat cycles was collected in Table A.4 (for muscle 1), A.5 (for muscle 2), and A.6 (for muscle 3).

Table A.4: Average Energy for Muscle 1 of CON and OR Group

Subject	Descending	Stationary	Ascending	Average Energy
CON				
1	34.821	28.937	47.165	36.974
2	40.428	43.197	44.544	42.723
5	42.700	36.855	48.691	42.749
6	41.011	41.807	41.703	41.507
7	41.180	34.774	59.151	45.035
10	29.935	65.633	44.656	46.742
11	34.709	18.791	51.679	35.060
12	27.395	16.200	55.434	33.010
15	35.523	35.940	52.381	41.281
17	44.621	57.504	46.546	49.557
19	41.394	40.440	42.369	41.401
20	34.317	44.924	52.163	43.801
22	40.844	31.784	44.238	38.956
23	20.843	50.942	51.924	41.236
24	24.111	30.651	36.600	30.454
25	83.975	86.779	67.249	79.334
OR				
3	40.507	42.874	51.114	44.832
8	33.274	45.506	40.249	39.676
9	29.972	41.519	39.851	37.114
13	29.960	35.027	50.869	38.619
14	30.211	17.301	52.477	33.330
16	57.215	23.221	42.312	40.916
18	25.014	21.505	38.120	28.209
21	23.002	49.830	45.561	39.464
27	40.816	35.219	53.997	43.344
28	51.969	25.079	35.288	37.445
29	28.809	48.809	52.186	43.268
30	40.138	64.222	42.989	49.116

Table A.5: Average Energy for Muscle 2 of CON and OR Group

Subject	Descending	Stationary	Ascending	Average Energy
CON				
1	46.301	33.355	44.453	41.370
2	44.891	30.897	49.625	41.804
5	51.561	20.806	43.936	38.768
6	58.466	46.951	48.699	51.372
7	42.844	68.753	27.690	46.429
10	47.135	41.739	34.892	41.256
11	44.020	24.313	51.362	39.898
12	34.282	34.522	37.990	35.598
15	37.376	62.156	41.907	47.146
17	37.008	53.272	40.148	43.476
19	48.560	35.681	37.916	40.719
20	29.409	31.572	45.075	35.352
22	42.725	31.367	46.910	40.334
23	27.970	63.559	48.762	46.763
24	51.816	29.098	50.855	43.923
25	46.676	51.640	41.822	46.713
OR				
3	65.335	14.629	63.650	47.871
8	4.457	37.148	47.399	39.668
9	53.844	69.241	57.732	60.272
13	48.676	46.904	65.926	53.835
14	44.611	68.225	37.629	50.155
16	47.937	58.787	44.192	50.305
18	39.019	21.140	34.374	31.511
21	55.791	49.155	23.395	42.780
27	38.200	62.166	33.639	44.668
28	48.723	26.202	47.649	40.858
29	31.079	42.749	37.554	37.127
30	62.479	43.051	55.622	53.717

Table A.6: Average Energy for Muscle 3 of CON and OR Group

Subject	Descending	Stationary	Ascending	Average Energy
CON				
1	33.417	33.897	48.612	38.642
2	43.023	25.366	47.628	38.672
5	39.288	38.864	55.221	44.458
6	60.512	39.533	45.451	48.499
7	39.974	28.444	53.880	40.766
10	54.559	38.159	48.273	46.997
11	44.214	53.758	44.176	47.383
12	40.967	35.514	37.913	38.131
15	39.586	44.222	46.045	43.284
17	46.372	50.034	60.862	52.423
19	47.197	39.787	38.417	41.800
20	51.378	43.229	64.525	53.044
22	45.996	26.917	54.128	42.347
23	39.772	53.031	57.622	50.142
24	54.910	34.084	55.928	48.307
25	37.046	59.337	50.806	49.063
OR				
3	37.977	59.146	35.223	44.115
8	41.644	29.465	42.929	38.013
9	43.886	51.979	44.223	46.696
13	52.162	40.540	40.289	44.331
14	42.411	52.464	40.796	45.223
16	56.530	47.099	45.627	49.752
18	45.523	58.988	56.995	53.835
21	43.136	66.346	41.533	50.338
27	45.996	35.458	50.720	44.058
28	40.034	45.528	47.400	44.321
29	59.442	38.627	43.130	47.066
30	81.126	76.039	52.082	69.749

Wavelet Power Spectrum

Muscle 1 - CON:

Tables A.7- A.22 show the power values for muscle 1 of CON group after 5 decomposition levels.

Table A.7: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 1

	Level 1	Level 2	Level 3	Level 4	Level 5
D	15.234	21.183	25.326	27.768	28.379
S	4.848	7.634	12.941	17.722	18.016
A	58.217	78.200	130.362	157.882	154.783

Table A.8: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 2

	Level 1	Level 2	Level 3	Level 4	Level 5
D	5.887	7.406	9.834	12.364	12.442
S	0.669	1.131	1.449	1.899	2.529
A	42.010	59.763	104.155	111.192	112.685

Table A.9: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 3

	Level 1	Level 2	Level 3	Level 4	Level 5
D	1.705	2.287	3.041	3.271	3.485
S	0.178	0.398	0.5738	0.754	0.843
A	16.512	24.076	37.216	32.518	32.220

Table A.10: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 4

	Level 1	Level 2	Level 3	Level 4	Level 5
D	2.717	3.585	4.997	5.605	5.507
S	3.257	4.778	6.139	6.962	7.358
A	81.265	115.329	172.295	229.732	224.537

Table A.11: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 5

	Level 1	Level 2	Level 3	Level 4	Level 5
D	9.840	14.117	19.819	20.992	20.308
S	1.154	2.263	3.452	4.022	4.285
A	147.440	192.286	315.352	281.735	263.630

Table A.12: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 6

	Level 1	Level 2	Level 3	Level 4	Level 5
D	6.342	8.403	12.645	13.330	13.906
S	0.660	0.934	1.617	2.027	2.347
A	45.485	57.485	103.298	104.419	94.439

Table A.13: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 7

	Level 1	Level 2	Level 3	Level 4	Level 5
D	13.331	18.071	27.209	30.189	29.212
S	2.211	3.260	5.651	8.687	9.246
A	32.728	42.676	68.701	79.405	73.886

Table A.14: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 8

	Level 1	Level 2	Level 3	Level 4	Level 5
D	6.338	8.009	12.342	11.949	12.260
S	1.115	1.8246	2.657	3.217	3.753
A	69.142	88.967	147.776	192.049	178.097

Table A.15: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 9

	Level 1	Level 2	Level 3	Level 4	Level 5
D	13.698	18.6612	24.958	29.426	31.986
S	3.834	5.7188	7.303	9.745	14.457
A	84.277	120.986	182.845	166.209	160.437

Table A.16: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 10

	Level 1	Level 2	Level 3	Level 4	Level 5
D	5.859	9.586	13.084	12.921	12.886
S	0.507	0.754	1.286	1.593	1.642
A	42.138	57.165	95.210	114.783	110.769

Table A.17: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 11

	Level 1	Level 2	Level 3	Level 4	Level 5
D	139.459	115.851	159.940	169.901	172.494
S	61.049	55.492	75.757	78.979	79.9168
A	593.848	803.997	1222.185	1464.309	1383.084

Table A.18: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 12

	Level 1	Level 2	Level 3	Level 4	Level 5
D	8.143	10.336	14.402	16.052	15.823
S	0.625	0.816	1.292	1.566	1.675
A	166.033	249.799	379.322	381.062	374.548

Table A.19: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 13

	Level 1	Level 2	Level 3	Level 4	Level 5
D	4.006	5.690	8.551	9.019	9.386
S	0.429	0.743	1.341	1.527	2.116
A	9.098	12.177	23.103	32.680	33.683

Table A.20: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 14

	Level 1	Level 2	Level 3	Level 4	Level 5
D	2.367	2.881	3.739	4.284	5.080
S	2.436	5.996	17.040	25.856	31.524
A	131.616	208.267	305.145	294.823	288.415

Table A.21: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 15

	Level 1	Level 2	Level 3	Level 4	Level 5
D	6.169	8.179	10.085	10.465	11.390
S	0.404	0.617	0.840	1.097	1.350
A	12.270	15.614	21.767	21.735	20.899

Table A.22: Wavelet Power Spectrum Calculations for Muscle 1-CON Subjects 16

	Level 1	Level 2	Level 3	Level 4	Level 5
D	10.466	14.529	32.184	34.474	34.697
S	1.235	1.938	4.913	6.624	6.745
A	14.703	20.507	36.173	39.469	39.015

Muscle 1 - OR:

Tables A.23- A.34 illustrate the power values for muscle 1 of OR group.

Table A.23: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 1

	Level 1	Level 2	Level 3	Level 4	Level 5
D	15.873	22.844	26.115	28.629	29.046
S	0.676	1.149	1.852	2.6107	3.953
A	33.964	47.320	75.404	74.402	73.645

Table A.24: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 2

	Level 1	Level 2	Level 3	Level 4	Level 5
D	4.897	6.234	7.728	8.162	8.667
S	1.083	1.525	3.229	4.137	4.935
A	220.683	282.050	495.946	604.871	578.224

Table A.25: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 3

	Level 1	Level 2	Level 3	Level 4	Level 5
D	968.466	1352.904	2125.791	2443.927	2378.981
S	403.874	647.025	1112.626	1728.159	2009.300
A	935.557	1426.209	2206.506	2312.612	2271.503

Table A.26: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 4

	Level 1	Level 2	Level 3	Level 4	Level 5
D	7.544	9.566	11.586	12.037	12.321
S	0.538	0.877	1.182	1.969	2.769
A	34.007	45.324	77.463	88.965	91.871

Table A.27: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 5

	Level 1	Level 2	Level 3	Level 4	Level 5
D	4.204	6.133	8.652	8.171	8.081
S	0.552	1.011	1.232	1.266	1.389
A	32.205	43.242	77.507	101.661	98.930

Table A.28: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 6

	Level 1	Level 2	Level 3	Level 4	Level 5
D	11.203	16.052	22.063	23.174	23.617
S	0.372	0.617	1.020	1.420	1.435
A	53.215	75.828	116.701	119.300	122.110

Table A.29: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 7

	Level 1	Level 2	Level 3	Level 4	Level 5
D	0.904	1.189	1.646	1.863	1.888
S	0.124	0.216	0.396	0.559	0.693
A	19.125	29.149	40.867	49.071	48.911

Table A.30: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 8

	Level 1	Level 2	Level 3	Level 4	Level 5
D	11.881	17.341	21.973	24.537	25.443
S	1.3618	2.155	2.250	2.334	2.845
A	141.249	195.605	318.413	297.099	295.917

Table A.31: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 9

	Level 1	Level 2	Level 3	Level 4	Level 5
D	25.499	39.360	57.141	55.785	57.272
S	1.0288	1.531	1.937	2.417	2.885
A	64.196	104.794	146.255	142.901	155.987

Table A.32: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 10

	Level 1	Level 2	Level 3	Level 4	Level 5
D	15.106	19.112	22.409	24.782	25.494
S	1.380	1.976	3.609	4.476	5.016
A	73.372	98.384	165.753	177.427	169.235

Table A.33: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 11

	Level 1	Level 2	Level 3	Level 4	Level 5
D	215.074	296.882	474.623	427.348	417.509
S	208.844	362.480	380.454	449.010	581.087
A	1189.976	2086.568	2735.580	2762.507	2778.652

Table A.34: Wavelet Power Spectrum Calculations for Muscle 1-OR Subjects 12

	Level 1	Level 2	Level 3	Level 4	Level 5
D	20423.076	30702.608	44432.748	40900.063	45473.032
S	2053.197	3491.464	6767.1330	10099.479	10841.255
A	11135.299	17183.720	22277.281	21759.664	21338.019

Muscle 2 - CON:

Tables A.35 - A.50 indicate the power values for muscle 2 of CON group.

Table A.35: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 1

	Level 1	Level 2	Level 3	Level 4	Level 5
D	77.188	119.487	164.128	153.089	150.122
S	4.224	6.686	11.103	12.400	14.202
A	16.189	25.187	36.740	42.413	45.409

Table A.36: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 2

	Level 1	Level 2	Level 3	Level 4	Level 5
D	20.990	26.399	35.836	46.449	39.715
S	0.025	0.043	0.058	0.078	0.104
A	2.244	2.593	3.320	4.911	3.860

Table A.37: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 3

	Level 1	Level 2	Level 3	Level 4	Level 5
D	3.009	5.015	6.416	6.643	7.284
S	0.806	1.274	2.413	3.575	4.085
A	1.185	1.822	2.381	2.287	2.288

Table A.38: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 4

	Level 1	Level 2	Level 3	Level 4	Level 5
D	22.319	31.656	46.558	55.991	52.927
S	52.990	82.217	117.911	144.729	158.481
A	11.905	16.976	32.807	47.837	50.425

Table A.39: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 5

	Level 1	Level 2	Level 3	Level 4	Level 5
D	49.357	71.623	114.343	128.904	121.670
S	3.532	5.519	7.761	9.022	9.828
A	267.821	344.736	567.003	638.628	564.952

Table A.40: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 6

	Level 1	Level 2	Level 3	Level 4	Level 5
D	477.181	668.557	1033.859	1515.541	1417.036
S	36.372	72.027	132.552	177.622	237.104
A	186.516	241.746	378.406	458.924	438.743

Table A.41: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 7

	Level 1	Level 2	Level 3	Level 4	Level 5
D	6.103	9.154	15.058	15.201	14.769
S	0.781	1.245	1.951	2.276	2.374
A	10.135	15.562	21.699	21.514	20.754

Table A.42: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 8

	Level 1	Level 2	Level 3	Level 4	Level 5
D	42.110	57.979	91.999	88.652	83.984
S	25.578	42.268	115.894	187.959	192.714
A	59.307	87.130	159.763	207.698	288.991

Table A.43: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 9

	Level 1	Level 2	Level 3	Level 4	Level 5
D	0.680	1.009	1.314	1.388	1.397
S	0.249	0.347	0.425	0.460	0.480
A	1.132	1.583	2.285	2.330	2.342

Table A.44: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 10

	Level 1	Level 2	Level 3	Level 4	Level 5
D	13.342	21.183	26.091	25.816	25.561
S	1.134	2.591	3.384	3.823	3.864
A	11.156	15.723	24.029	25.276	26.616

Table A.45: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 11

	Level 1	Level 2	Level 3	Level 4	Level 5
D	138.710	202.048	285.997	295.704	293.425
S	183.614	267.888	306.420	323.075	317.885
A	92.518	126.435	192.791	230.787	236.527

Table A.46: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 12

	Level 1	Level 2	Level 3	Level 4	Level 5
D	27.124	34.187	50.642	56.277	60.207
S	1.849	2.975	4.373	6.403	6.676
A	18.290	24.362	39.424	46.338	45.089

Table A.47: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 13

	Level 1	Level 2	Level 3	Level 4	Level 5
D	9.798	16.314	19.753	19.312	19.549
S	2.041	3.398	3.510	3.975	4.553
A	49.894	84.482	89.872	88.383	89.000

Table A.48: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 14

	Level 1	Level 2	Level 3	Level 4	Level 5
D	10.454	12.868	17.524	19.998	20.754
S	0.510	0.895	3.186	5.488	5.866
A	2.827	4.159	6.142	6.321	6.699

Table A.49: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 15

	Level 1	Level 2	Level 3	Level 4	Level 5
D	148.435	233.150	340.468	295.913	295.245
S	4.451	6.602	11.455	15.892	20.992
A	125.629	193.948	268.378	271.082	267.695

Table A.50: Wavelet Power Spectrum Calculations for Muscle 2-CON Subjects 16

	Level 1	Level 2	Level 3	Level 4	Level 5
D	10.752	14.802	21.200	27.848	26.360
S	1.097	1.698	2.161	2.278	2.420
A	10.717	15.638	22.129	23.642	22.596

Muscle 2 - OR:

Tables A.51 - A.62 show the power for muscle 2 of OR group.

Table A.51: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 1

	Level 1	Level 2	Level 3	Level 4	Level 5
D	9.166	13.820	15.052	14.768	14.948
S	0.640	1.361	3.681	5.734	6.262
A	4.393	6.175	8.715	8.910	8.826

Table A.52: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 2

	Level 1	Level 2	Level 3	Level 4	Level 5
D	10.424	15.486	19.268	20.263	22.215
S	3.239	5.794	6.606	8.119	8.875
A	43.230	60.027	73.495	73.003	72.547

Table A.53: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 3

	Level 1	Level 2	Level 3	Level 4	Level 5
D	37.060	53.131	65.017	68.115	69.114
S	9.807	14.002	24.005	31.272	32.134
A	138.355	187.669	220.631	224.287	224.146

Table A.54: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 4

	Level 1	Level 2	Level 3	Level 4	Level 5
D	37.490	57.201	75.941	81.755	80.911
S	3.568	6.550	11.072	15.997	22.838
A	18.086	26.652	43.978	50.092	53.315

Table A.55: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 5

	Level 1	Level 2	Level 3	Level 4	Level 5
D	24.240	34.871	44.438	80.933	74.366
S	0.113	0.215	0.328	0.469	0.724
A	3.826	4.849	8.846	14.691	13.804

Table A.56: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 6

	Level 1	Level 2	Level 3	Level 4	Level 5
D	693.748	1203.845	1609.567	1634.089	1780.215
S	62.969	100.897	171.008	252.983	288.864
A	613.058	1001.713	1350.991	1264.552	1235.940

Table A.57: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 7

	Level 1	Level 2	Level 3	Level 4	Level 5
D	535.898	841.020	1113.662	1173.318	1174.668
S	168.207	284.598	509.621	626.983	640.425
A	168.908	277.864	443.648	551.551	572.558

Table A.58: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 8

	Level 1	Level 2	Level 3	Level 4	Level 5
D	8.141	11.204	19.938	18.650	18.294
S	3.816	6.239	15.481	19.927	25.001
A	10.376	15.026	28.075	32.724	32.730

Table A.59: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 9

	Level 1	Level 2	Level 3	Level 4	Level 5
D	6.581	8.447	12.402	11.712	11.499
S	6.641	9.551	15.499	18.320	18.653
A	9.148	13.946	19.090	18.491	18.840

Table A.60: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 10

	Level 1	Level 2	Level 3	Level 4	Level 5
D	50.262	85.738	124.497	141.650	143.019
S	6.847	12.284	21.693	22.810	26.116
A	21.782	26.181	34.242	46.903	67.909

Table A.61: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 11

	Level 1	Level 2	Level 3	Level 4	Level 5
D	3.548	4.664	6.297	5.791	5.785
S	0.156	0.203	0.300	0.327	0.410
A	21.679	36.177	45.961	48.347	48.676

Table A.62: Wavelet Power Spectrum Calculations for Muscle 2-OR Subjects 12

	Level 1	Level 2	Level 3	Level 4	Level 5
D	42.547	59.336	118.987	119.000	129.684
S	7.721	13.829	18.217	22.227	26.778
A	64.900	88.085	142.020	136.315	131.877

Muscle 3 - CON:

Tables A.63 - A.78 indicate the power values for muscle 3 of CON group.

Table A.63: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 1

	Level 1	Level 2	Level 3	Level 4	Level 5
D	497.076	822.457	808.660	800.428	795.611
S	2.773	4.797	7.064	8.859	10.795
A	162.498	260.785	342.708	331.838	333.221

Table A.64: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 2

	Level 1	Level 2	Level 3	Level 4	Level 5
D	326.453	534.807	644.757	637.505	632.421
S	48.383	95.583	112.166	117.314	129.691
A	91.764	155.638	167.959	166.553	168.692

Table A.65: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 3

	Level 1	Level 2	Level 3	Level 4	Level 5
D	124.233	227.332	265.344	271.912	285.654
S	54.618	97.620	135.054	151.085	163.683
A	82.432	130.924	164.939	163.833	164.820

Table A.66: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 4

	Level 1	Level 2	Level 3	Level 4	Level 5
D	87.126	139.155	156.492	166.458	172.873
S	175.566	277.305	306.601	344.573	365.555
A	35.767	68.836	122.789	159.686	176.755

Table A.67: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 5

	Level 1	Level 2	Level 3	Level 4	Level 5
D	36.427	55.111	84.935	92.454	89.458
S	6.363	12.497	15.455	17.910	22.549
A	34.615	52.456	81.618	80.382	77.213

Table A.68: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 6

	Level 1	Level 2	Level 3	Level 4	Level 5
D	178.423	287.304	375.901	364.661	353.847
S	20.020	47.380	103.189	152.773	190.989
A	138.541	207.449	361.070	356.026	368.845

Table A.69: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 7

	Level 1	Level 2	Level 3	Level 4	Level 5
D	703.160	1136.565	1664.831	1531.623	1523.088
S	80.780	143.932	229.145	274.731	335.666
A	638.971	1006.164	1181.079	1243.186	1235.578

Table A.70: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 8

	Level 1	Level 2	Level 3	Level 4	Level 5
D	391.437	676.167	1092.431	1305.961	1367.200
S	189.154	340.897	472.470	554.419	694.553
A	465.481	803.266	991.217	965.769	992.540

Table A.71: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 9

	Level 1	Level 2	Level 3	Level 4	Level 5
D	155.602	250.867	294.101	336.021	347.326
S	69.496	102.568	134.358	132.356	142.275
A	47.149	85.434	103.584	113.534	121.371

Table A.72: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 10

	Level 1	Level 2	Level 3	Level 4	Level 5
D	625.449	1063.203	1146.037	1168.231	1171.506
S	68.033	149.599	161.139	174.247	176.196
A	138.174	226.250	359.235	432.702	441.502

Table A.73: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 11

	Level 1	Level 2	Level 3	Level 4	Level 5
D	560.791	955.831	1058.664	1020.265	1014.233
S	1048.788	1763.070	2166.920	2198.518	2242.857
A	157.841	231.215	259.253	259.598	267.300

Table A.74: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 12

	Level 1	Level 2	Level 3	Level 4	Level 5
D	1158.028	1934.565	3208.305	3047.031	3050.432
S	314.863	574.048	940.482	1487.251	1746.079
A	371.082	564.203	846.181	807.819	827.573

Table A.75: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 13

	Level 1	Level 2	Level 3	Level 4	Level 5
D	625.975	995.065	1275.756	1166.583	1169.189
S	74.664	132.690	179.696	218.048	287.688
A	317.583	551.739	820.001	871.994	877.837

Table A.76: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 14

	Level 1	Level 2	Level 3	Level 4	Level 5
D	189.419	285.742	312.286	324.986	338.000
S	37.167	105.513	166.226	184.567	219.616
A	69.331	125.254	226.561	281.302	288.809

Table A.77: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 15

	Level 1	Level 2	Level 3	Level 4	Level 5
D	71.660	114.217	155.192	153.889	154.763
S	1.351	2.280	4.045	5.964	7.392
A	64.100	102.363	144.907	126.139	126.353

Table A.78: Wavelet Power Spectrum Calculations for Muscle 3-CON Subjects 16

	Level 1	Level 2	Level 3	Level 4	Level 5
D	623.189	1029.776	1299.165	1269.022	1265.944
S	198.519	302.462	629.635	836.473	953.208
A	571.017	937.823	1089.158	1091.524	1124.257

Muscle 3 - OR:

Tables A.79 - A.90 show the power values for muscle 3 of OR group.

Table A.79: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 1

	Level 1	Level 2	Level 3	Level 4	Level 5
D	241.137	405.907	468.854	476.776	470.264
S	55.161	92.033	160.331	189.950	199.877
A	905.491	1494.067	1849.520	1746.178	1732.128

Table A.80: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 2

	Level 1	Level 2	Level 3	Level 4	Level 5
D	209.650	356.795	366.922	351.304	350.055
S	65.453	135.278	210.988	261.701	292.567
A	400.546	605.973	723.068	818.077	823.966

Table A.81: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 3

	Level 1	Level 2	Level 3	Level 4	Level 5
D	1.493	1.317	1.876	1.917	1.902
S	0.371	0.337	0.466	0.483	0.497
A	5.515	7.326	11.799	11.818	11.417

Table A.82: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 4

	Level 1	Level 2	Level 3	Level 4	Level 5
D	821.632	1518.069	1669.291	1717.896	1766.572
S	187.145	514.404	1105.047	1480.271	1524.736
A	188.328	312.572	491.248	634.088	657.874

Table A.83: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 5

	Level 1	Level 2	Level 3	Level 4	Level 5
D	545.719	865.051	1103.135	1005.195	978.251
S	37.543	73.965	195.079	296.906	342.106
A	160.038	233.738	334.886	396.874	418.170

Table A.84: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 6

	Level 1	Level 2	Level 3	Level 4	Level 5
D	261.641	464.855	579.377	562.829	567.709
S	39.149	68.106	116.491	145.394	196.061
A	346.235	619.076	819.979	790.901	812.253

Table A.85: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 7

	Level 1	Level 2	Level 3	Level 4	Level 5
D	146.493	241.115	258.398	248.978	248.341
S	16.975	31.099	27.700	28.182	31.674
A	82.070	133.048	152.403	152.109	151.216

Table A.86: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 8

	Level 1	Level 2	Level 3	Level 4	Level 5
D	272.998	487.699	568.959	546.757	556.395
S	191.790	393.960	535.219	600.226	705.901
A	200.804	279.040	353.518	346.098	360.644

Table A.87: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 9

	Level 1	Level 2	Level 3	Level 4	Level 5
D	101.237	199.715	202.218	204.034	205.073
S	127.145	209.465	240.019	249.851	257.056
A	92.910	154.030	162.055	175.929	183.816

Table A.88: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 10

	Level 1	Level 2	Level 3	Level 4	Level 5
D	656.948	1091.735	1358.654	1369.095	1362.085
S	59.806	114.845	241.148	369.472	387.917
A	208.228	326.177	407.325	401.511	399.296

Table A.89: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 11

	Level 1	Level 2	Level 3	Level 4	Level 5
D	0.900	0.844	1.243	1.270	1.321
S	0.150	0.166	0.288	0.372	0.430
A	4.821	6.022	9.874	10.793	9.689

Table A.90: Wavelet Power Spectrum Calculations for Muscle 3-OR Subjects 12

	Level 1	Level 2	Level 3	Level 4	Level 5
D	15.952	19.053	39.267	39.485	39.550
S	1.500	2.011	5.307	7.370	7.729
A	14.054	14.865	23.447	25.729	25.945

Ratio of Ascending Over Descending Phase

Muscle 1 - CON:

Table A.91: Ratio of A/D for Muscle 1 of CON subjects

Subject	Level 1	Level 2	Level 3	Level 4	Level 5
1	3.822	3.692	5.147	5.686	5.454
2	7.136	8.070	10.591	8.993	9.057
3	9.687	10.526	12.238	9.942	9.246
4	29.914	32.168	34.478	40.984	40.771
5	14.984	13.621	15.911	13.421	12.982
6	7.172	6.841	8.169	7.833	6.791
7	2.455	2.362	2.525	2.630	2.529
8	10.909	11.108	11.973	16.073	14.527
9	6.152	6.483	7.326	5.648	5.016
10	7.192	5.963	7.277	8.883	8.596
11	4.258	6.940	7.642	8.619	8.018
12	20.389	24.169	26.338	23.739	23.671
13	2.271	2.140	2.702	3.623	3.589
14	55.605	72.296	81.603	68.821	56.772
15	1.989	1.909	2.158	2.077	1.835
16	1.405	1.412	1.124	1.145	1.124

Muscle 1 - OR:

Table A.92: Ratio of A/D for Muscle 1 of OR subjects

Subject	Level 1	Level 2	Level 3	Level 4	Level 5
1	2.140	2.071	2.887	2.599	2.535
2	45.068	45.246	64.179	74.109	66.716
3	0.966	1.054	1.038	0.946	0.955
4	4.508	4.738	6.686	7.391	7.456
5	7.661	7.050	8.958	12.441	12.242
6	4.750	4.724	5.290	5.148	5.170
7	21.163	24.523	24.822	26.346	25.905
8	11.889	11.280	14.491	12.108	11.631
9	2.518	2.662	2.560	2.562	2.724
10	4.857	5.148	7.397	7.160	6.638
11	5.533	7.028	5.764	6.464	6.655
12	0.545	0.560	0.501	0.532	0.469

Muscle 2 - CON:

Table A.93: Ratio of A/D for Muscle 2 of CON subjects

Subject	Level 1	Level 2	Level 3	Level 4	Level 5
1	0.210	0.211	0.224	0.277	0.302
2	0.107	0.098	0.093	0.106	0.097
3	0.394	0.363	0.371	0.344	0.314
4	0.533	0.536	0.705	0.854	0.953
5	5.426	4.813	4.959	4.954	4.643
6	0.391	0.362	0.366	0.303	0.310
7	1.661	1.700	1.441	1.415	1.405
8	1.408	1.503	1.737	2.343	3.441
9	1.665	1.570	1.739	1.678	1.676
10	0.836	0.742	0.921	0.979	1.041
11	0.667	0.626	0.674	0.780	0.806
12	0.674	0.713	0.778	0.823	0.749
13	5.092	5.179	4.550	4.577	4.553
14	0.270	0.323	0.351	0.316	0.323
15	0.846	0.832	0.788	0.916	0.907
16	0.997	1.056	1.044	0.849	0.857

Muscle 2 - OR:

Table A.94: Ratio of A/D for Muscle 2 of OR subjects

Subject	Level 1	Level 2	Level 3	Level 4	Level 5
1	0.479	0.447	0.579	0.603	0.590
2	4.147	3.876	3.814	3.603	3.266
3	3.733	3.532	3.393	3.293	3.243
4	0.482	0.466	0.579	0.613	0.659
5	0.158	0.139	0.199	0.182	0.186
6	0.884	0.832	0.839	0.774	0.694
7	0.315	0.330	0.398	0.470	0.487
8	1.275	1.341	1.408	1.755	1.789
9	1.390	1.651	1.539	1.579	1.638
10	0.433	0.305	0.275	0.331	0.475
11	6.110	7.757	7.299	8.349	8.414
12	1.525	1.485	1.194	1.146	1.017

Muscle 3 - CON:

Table A.95: Ratio of A/D for Muscle 3 of CON subjects

Subject	Level 1	Level 2	Level 3	Level 4	Level 5
1	0.327	0.317	0.424	0.415	0.419
2	0.281	0.291	0.260	0.261	0.267
3	0.664	0.576	0.621	0.603	0.577
4	0.411	0.495	0.785	0.959	1.022
5	0.950	0.952	0.961	0.869	0.863
6	0.776	0.722	0.961	0.976	1.042
7	0.909	0.885	0.709	0.812	0.811
8	1.189	1.188	0.907	0.740	0.726
9	0.303	0.341	0.352	0.338	0.349
10	0.221	0.213	0.313	0.370	0.377
11	0.281	0.242	0.245	0.254	0.264
12	0.320	0.292	0.264	0.265	0.271
13	0.507	0.554	0.643	0.747	0.751
14	0.366	0.438	0.725	0.866	0.854
15	0.894	0.896	0.934	0.820	0.816
16	0.916	0.911	0.838	0.860	0.888

Muscle 3 - OR:

Table A.96: Ratio of A/D for Muscle 3 of OR subjects

Subject	Level 1	Level 2	Level 3	Level 4	Level 5
1	3.755	3.681	3.945	3.662	3.683
2	1.911	1.698	1.971	2.329	2.354
3	3.695	5.562	6.291	6.164	6.003
4	0.229	0.206	0.294	0.369	0.372
5	0.293	0.270	0.304	0.395	0.427
6	1.323	1.332	1.415	1.405	1.431
7	0.560	0.552	0.590	0.611	0.609
8	0.736	0.572	0.621	0.633	0.648
9	0.918	0.771	0.801	0.862	0.896
10	0.317	0.299	0.300	0.293	0.293
11	5.360	7.137	7.946	8.498	7.335
12	0.881	0.780	0.597	0.652	0.656

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