APPOXIMATE ENTROPY IN ELECTROMYOGRAPHY DURING MUSCLE FATIGUE

by

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APPROVAL PAGE

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APPOXIMATE ENTROPY IN ELECTROMYOGRAPHY DURING MUSCLE FATIGUE

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M. S. Thesis - Computer Engineering
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ABSTRACT

Muscle fatigue (MF) is a phenomenon that involves the decline of one's ability to perform physical action. The early detection of MF is important in the field of ergonomics, sports, occupational work, and human-computer interaction, as MF affects performance and may cause injury. Since MF is not a quantitative value, existing researches in this field are mostly based on different measurable parameters. Electromyography is among the most commonly used signals in analysing MF.

The main purpose of this thesis is to analyse MF during isometric contractions. For this purpose Discrete Wavelet Transform (DWT) is used to divide each signal to get sub-band frequencies. Approximate Entropy (ApEn) is applied to each sub-band. In the next step, each band is segmented into three sections. Finally, a comparison between the first segment and last segment is performed to evaluate MF.

Key words: Muscle Fatigue, Electromyography, Discrete Wavelet Transform, Approximate Entropy.

KAS YORGUNLUĞU ESNASINDA KAYDEDİLEN ELEKTROMİYOGRAFİ İŞARETLERİNDE YAKLAŞIK ENTROPİ

Payam Wali MUHAMMED HUSSEIN

Yüksek Lisans Tezi- Bilgisayar Mühendisliği
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Tez Danışmanı: Yrd. Doç. Kadir TUFAN

Eş Danışman: Yrd. Doç. Şükrü OKKESIM

ÖZ

Kas yorgunluğu, fiziksel aktivite gerçekleştiren bir kişinin bu işi yapabilme yeteneğini azaltan bir durumdur. Yapılan iş üzerindeki performansı etkilediği ve kazalara sebep olduğu için, kas yorgunluğunun erken teşhisi ergonomi, spor, mesleki iş ve insan-bilgisayar etkileşimi alanlarında önem arz eder. Kas yorgunluğunun nicel bir değer olmaması araştırmacıları farklı ölçülebilir parametreler kullanarak kas yorgunluğunu değerlendirmelerine yönelik çalışmalar yapmalarına sebep olmuştur. EMG, kas yorgunluğu analizinde en yaygın kullanılan sinyaller arasında yer almaktadır.

Bu çalışmanın amacı, izometrik kasılmalar esnasında kas yorgunluğunu analiz etmektir. Bu amaçla Ayrık Dalgacık Dönüşümü kullanılarak her bir sinyal alt bantlarına ayrıldı ve bu bantlara Yaklaşık Entropi uygulandı. Bir sonraki aşamada her bir bant üç sekmeye bölündü. Son olarak ilk sekme ve son sekme arasında karşılaştırma yapılarak kas yorgunluğu değerlendirildi

Anahtar Kelimeler: Kas yorgunlugu, Ayrık Dalgacık Dönüşümü, Yaklaşık Entropi.

To Avi and Nami, my blessings!

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SYMBOL/ABBREVIATION

ApEn	Approximate Entropy
ARV	Average Rectified Value
BB	Biceps Brachii
DWT	Discrete Wavelet Transform
EMG	Electromyogram
FFT	Fast Fourier Transform
MDF	Median Power Frequency
MF	Muscle Fatigue
MNF	Mean Power Frequency
RMS	Root Mean Square
TB	Triceps Brachii

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

The term Muscle Fatigue (MF) is used to express a decline in the capacity to perform physical action. Previously, MF had been known as a failure point during a contraction when the skeletal muscle cannot generate a required amount of muscle force [1]. Basically, during voluntary muscle contraction if the produced force is decreased then MF happens [2]. However, various reasons can cause MF, such as metabolic accumulation or generating improper motor commands in the motor cortex.

Researchers try to measure MF for the purpose of early detection due to its importance in the field of ergonomics, sports, occupational work, and human-computer interaction. Since MF affects performance and causes injury, creating a computerised system to anticipate and discover fatigue by warning the person is essential in increasing human performance during daily work, sport, and other manual activities. The system can also be applied in occupational health and ergonomics, especially where there is a risk related to occupation disorders in the muscular system. Localised MF may cause work-related injuries in employees, in particular when the required task needs high stationary muscle activity [3].

Research conducted by the Washington State Department of Labor and Industries, which is also mentioned by *Jones et al.* in their report, states that above 50% of labourers have faced musculoskeletal abnormalities, mainly during jobs that involve manual handling [4]. *Chaffin et al.'s* analysis of occupational biomechanics declares that overloading of muscle force is the main cause of MF, and moreover that it causes severe

MF, aching in muscles, and strict functional incapacity in muscles and other tissues of the human body [5]. Consequently, it is essential for ergonomists to find an effective method to predict occupational MF.

For the purpose of evaluating MF, it is important to obtain correct information from peoples' muscles. Therefore, an electromyography (EMG) is an essential tool for collecting signals, since it is the study of muscle electrical signals and is a method for assessing and recording the electrical activity produced by contraction and relaxation of muscle tissue. The EMG signal is a complex signal and is controlled by the nervous system. EMG directly looks inside the muscle and records the signals, which helps specialists to analyse these signals and detect muscular performance and medical abnormalities, which depend on structural and physiological properties of the muscles [6].

1.2 STATEMENT OF THE PROBLEM

Whilst there are some features to evaluate MF in the extant literature, most primarily concentrate on the clinical aspects and thus the parameters are insufficient to detect MF in its early stages or to evaluate the problem quantitatively. Therefore, in our research we try to find nonlinear features using Approximate Entropy (ApEn). First of all we divide our original signal using Discrete Wavelet Transform (DWT) for noise elimination and to get a sub-version, and then we compute the ApEn values of each approximation coefficient and detail coefficients. For computing the ApEn, we decided on the suggestions by Pincus in which the embedding dimension (m) is set to 2, and vector comparison distance (r) and time delay (t) set to 0.15 times the standard deviation [7].

1.3 PURPOSE OF THE STUDY

Most of the researches that evaluate MF are based on decreasing frequency and increasing amplitude in isometric muscle contractions. Formerly, quantification analyses of MF were performed by using linear methods in which some EMG

parameters were used such as Mean Power Frequency (MNF), Median Power Frequency (MDF), Root Mean Square (RMS), and Average Rectified Value (ARV) in which changes in these parameters are recorded by passing time [8,9].

The aim of this thesis is to analyse MF during isometric contractions using surface EMG. For this purpose a group of 30 young volunteers (15 females, 15 males) were recruited to our study. They were all healthy subjects without any history of previous injury, metabolic, or muscular disease. The biceps brachii (BB) and triceps brachii (TB) muscles were chosen for the test.

The organisation of this thesis is as follows: Chapter 2 provides an overview of MF, a description of the muscular system, and a historical background of EMG signal processing. Then Chapter 3 contains the material and methods used in our study. Chapter 4 is the discussion of the results, and Chapter 5 is the conclusion of our work.

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CHAPTER 2

LITERATURE REVIEW

2.1 MUSCULAR SYSTEM

The muscular system is a system within the human body that is made up of muscular tissues that work together with the skeletal system to control all bodily movements. Muscles are not only responsible for movements that are under the control of human will (voluntary movements) but also produce movements for involuntary activities that humans might not see or feel, such as food digestion, breathing, pumping blood, and other activities.

2.1. Function of the Muscular System

The muscular system performs essential functions in the body as follows:

- Production of heat: Muscle fibres generate large amounts of heat in the body by sliding against each other to maintain an acceptable level of heat to prevent physiological consequences.
- Body movement: Every movement of our body is controlled by skeletal muscles, including walking, running, writing, and talking. They provide the force for doing the activities by contracting.
- Give shape to the body: Skeletal muscles provide the human body with a stable and proper posture. They support the weak joints of the body to provide stability.
- Blood circulation: Pumping blood to other parts of the body is done through cardiac muscles.
- Digestion: The smooth muscles of the internal organs like the stomach and intestines are responsible for digesting food [10].

2.1.2 Muscle Tissue Types

The muscle tissues that build the body are made of special types of cells that are divided into three types (Figure 2.1):

a) Cardiac muscles: Cardiac muscles are the muscles that are exclusively part of the heart, which means they are not found in any other part of the body. Their motion is involuntary. They are extremely powerful and strong, and create rhythmic pulsing that pumps blood to the body through the signals they receive from the brain. They also create electrical impulses which contracts the heart.
b) Smooth muscles: These muscles build the wall of the soft body organs like the stomach, blood vessels, respiratory passages, and intestines. They are also involuntary muscles, smooth in shape under the microscope, and take part in digesting food in the stomach and flowing urine in the bladder.
c) Skeletal muscles: Skeletal muscles build most of the human body weight (about 40%). Unlike the cardiac and smooth muscles they are voluntary muscles and control all body movement [10, 11].

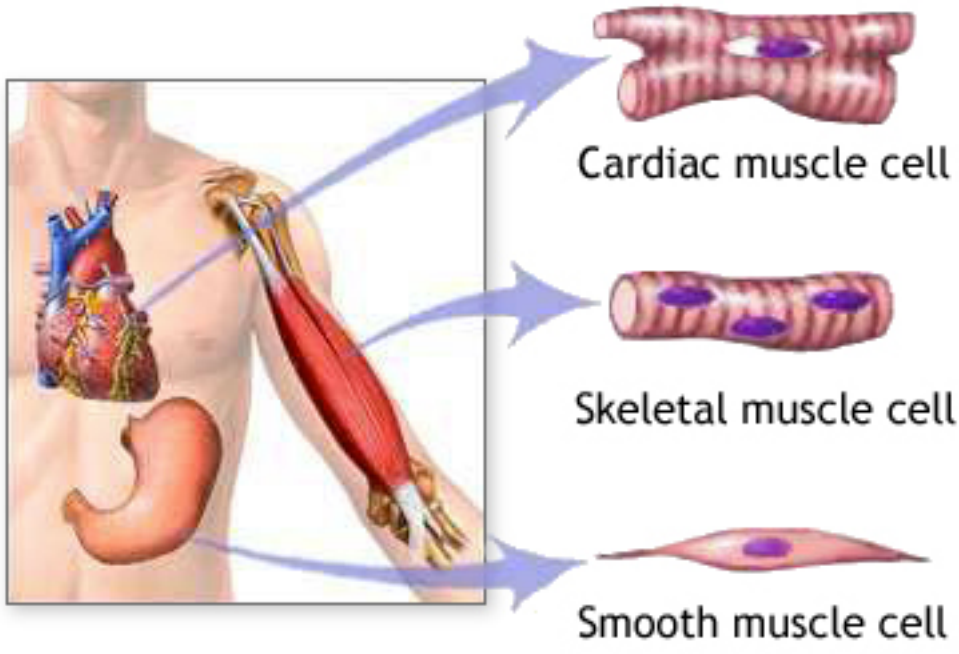

Figure 2.1 Structure of Muscle Tissue Type [12]

2.2 OVERVIEW OF MUSCLE FATIGUE

There are various definitions of MF and tools to analyse it scientifically. The features of MF are increase amplitude in the time domain and transition from high frequency to low frequency in the frequency domain. These changes are occurring on EMG signals, which affect different factors such as electrode type, surface of the skin, and the nature in which the signal is collected. In order to have a better understanding of this fact, the purpose of this section is to explain the anatomy of the muscular system, history of EMG, how to record EMG signals, and MF in the perspective of EMG.

2.3 ELECTROMYOGRAPHY AND HISTORICAL BACKGROUND

EMG is a method used for evaluating and recording the electrical motion produced by muscle contractions, and its recordings are called electromyograms. It can be used in different areas as shown in Figure 2.3. EMG is a powerful method that helps to look directly at the interior of a muscle and is also used in several investigative

domains including medical research, rehabilitation, ergonomics, and sports science [10].

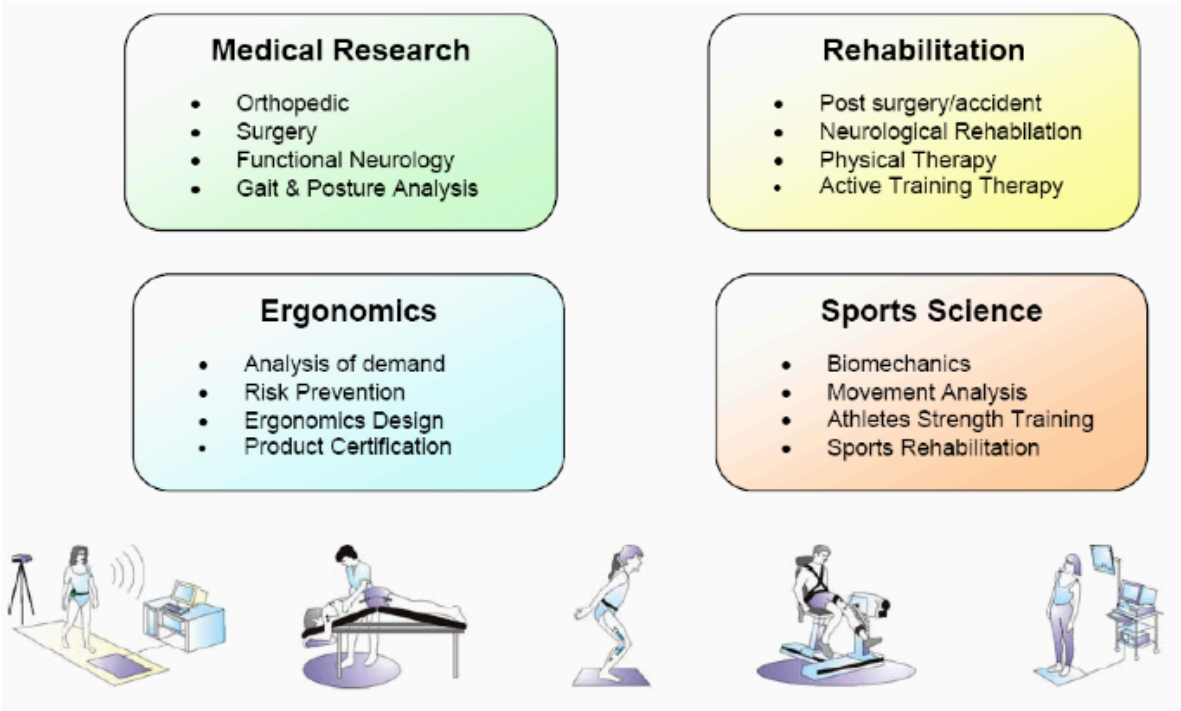

Figure 2.3 Application areas of EMG [10]

In 1666, Redi became the first scientist to discover EMG signals when he found that muscles generate electricity [11]. The expression of EMG showed up directly after the first record of muscle motion electricity through voluntary muscle contraction by Marey in 1890. This scientific innovation of Marey was dependent on an invention by Dubois-Raymonds at the beginning of the 19th century, in which he found that recording a voluntary muscle contraction's electricity can be done. During the 1960s, EMG's were used medically for the purpose of treating some detailed illnesses. Hardyck was among the doctors who used EMG signals for the first time in a clinical field [13].

Later on Basmajian, known as the father of EMG, established that subjects can control voluntary muscle contractions through the neuromuscular system even more deeply in the single motor unit [11, 13]. In 1965, he came up with the idea of collecting all of his work on EMG in a book [11], which was later modified by De Luca, becoming a reference guide in the area of EMG. Although De Luca, who is possibly the most significant scientist in the field of EMG, has insisted on the importance of understanding the weaknesses of EMG signals, he has also stated that although EMG is an easy instrument to use in the functional activity of muscles it might easily lead to misuse [11].

2.3.1 EMG Signal Generation

Understanding EMG signal generation is based on anatomic and functional knowledge of the neuromuscular system. The movement of muscles occurs through three phases: excitation, contraction, and relaxation. Muscles perform two types of movements, voluntary and involuntary, with the latter controlled by the nervous system and generated by cardiac and smooth muscles. On the other hand, voluntary movement is generated by skeletal muscles and its source is the action potential of the motor neurons [14]. Skeletal muscle is built up of a large number of generally parallel muscle cells called muscle fibres. Each fibre has electrical activity [15], which is derived from the motor unit (MU), the minimum functional unit of the muscle that is comprised of both neural and muscular components. Figure 2.4 is a simplified diagram of the MU. The muscular component of the MU contains all skeletal muscle fibres supplied by the axoChemical synapses bind the terminals of the motor axon to these bundles of fibres.

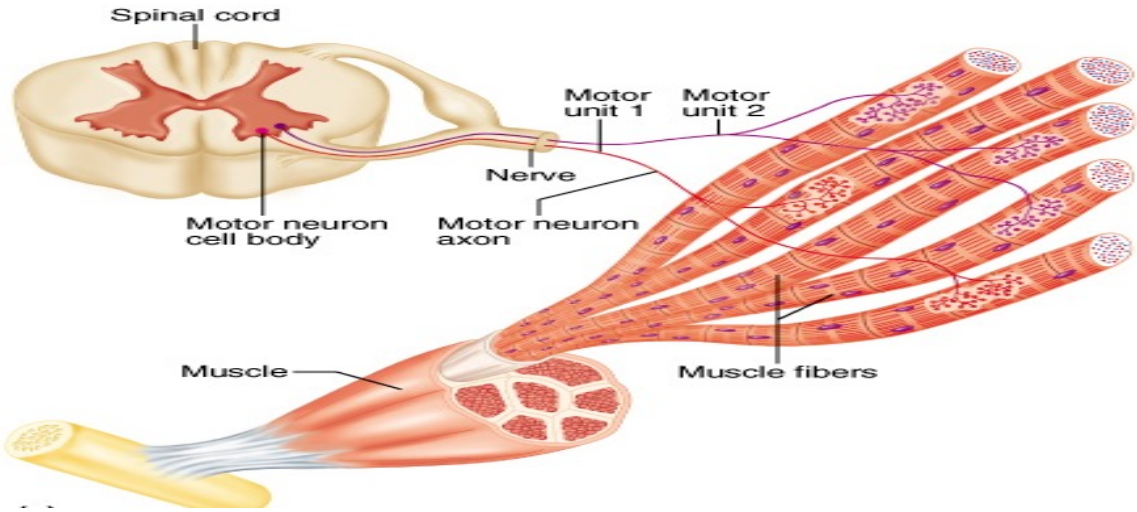

Figure 2.4 Simplified Diagram of Motor Unit [16]

Basically, from the physiological perspective the MU acts as a unit. The action potential is the basic factor in recording biomedical signals. It results from periodic impulses coming from the central nervous system. The action potentials happen when positive ions enter the cell and negative ions leave the cell. This increase of positive ions makes muscle fibres positive and this process happens in all muscle fibres, and as a result all muscle cells are excited at the same time in one MU. The output electrical current can be recorded by placing electrodes on the surface of the skin. At the end, EMG is produced which is a collection of electrical impulses from one or more MU [17]. Figure 2.5 is a raw EMG signal from our study.

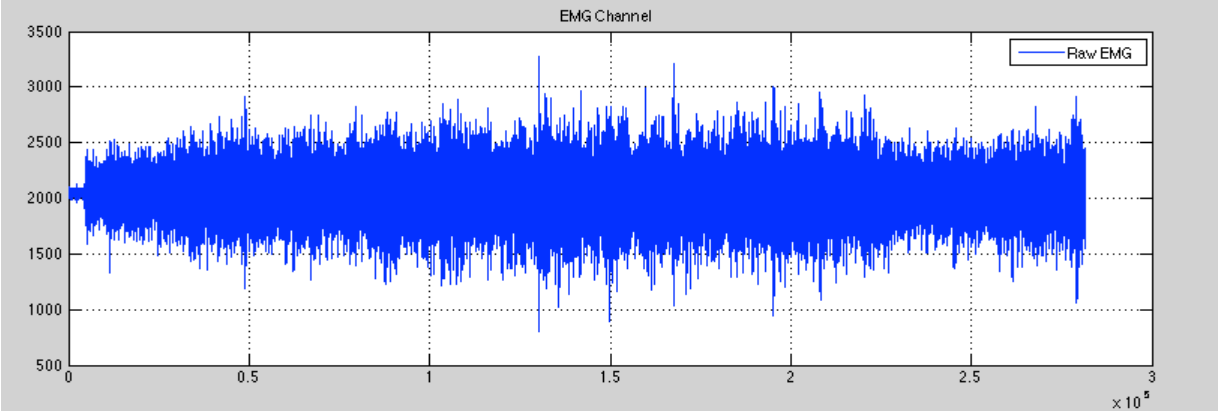

Figure 2.5 A Raw EMG of one volunteer's isometric contraction

2.3.2 Electrodes

The electrodes used in gathering data in EMG are two types (see Figure 2.6). The first type are invasive electrodes, in which a needle is inserted directly into the muscle, and the second type are surface electrodes that bind to the surface of the skin to collect electric sparks formed from muscle concentration [13]. However, only well-trained physical therapists can use invasive electrodes to choose the most proper location to insert the needle electrodes. Hence this is difficult in data collection for experimental use. On the other hand, the non-invasive electrode is a more usual tool labelled as surface EMG and is used for obtaining the signals from different areas of skin surface during both isometric and isotonic contractions [18].

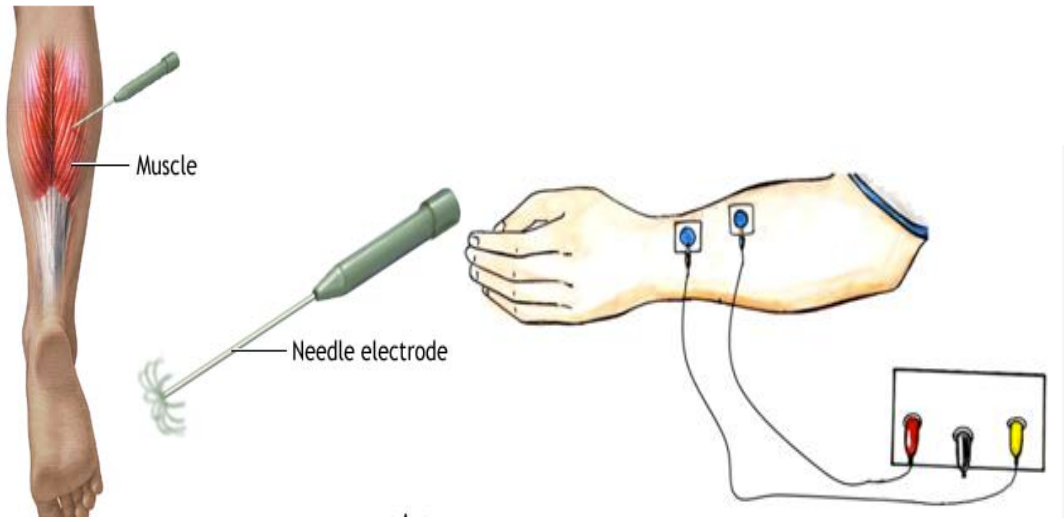

Figure 2.6 Types of electrodes [19]

2.4 MUSCLE FATIGUE IN EMG

EMG signals consist of information from the MU, and are good evidence for the identification of physiological and neural changes in the muscular system. The content of the signal is affected by some factors. Thus, it is nothing to do with the raw EMG signals unless suitable procedures and methods for EMG signal analysis are used [20, 21, 22].

The parameters of MF are increased amplitude in the time domain and declining frequency from high to low in the frequency domain. Nearly a century ago a professor named Piper performed an experiment and observed a certain decrease in the frequency component of surface myoelectric signals during isometric contraction [23, 24]. Cobb and Forbes also perceived an incline in amplitude, which is one sign of MF during an isometric muscle contraction. So, features of MF are increased amplitude in the time domain and transition from high frequency to low frequency in the frequency domain [25].

A signal is obtained and, in some environments, analysed in the time domain where the signal amplitude is denoted as a function of time. Still, for most of the signal analysis techniques, the frequency parameter is widely used, so the signal is evaluated

in the frequency domain. For the first time the ability to monitor MF through frequency analysis of myoelectric signals was provided by Kogi and Hakamada, who observed a decline in the frequency of the EMG signal [26]. As a result of increasing amplitude and decreasing frequency during MF, some parameters change. Researchers mostly focus on MNF and MDF, which are both frequency domain-related parameters. Hagberg states that if the amplitude of the EMG signal in the time domain inclines as MDF declines, there is definitely MF occurrence [27]. *Zaman et al*. depended on this hypothesis and analysed MF at different Maximum Voluntary Contractions (MVC). They concluded that at the end of their study the value of RMS increased, whereas MDF and MNF values decreased. In this study they published quantitative results [28].

DWT analysis is an alternative method to the time-varying signal analysis tool, in which a signal is decomposed to various components by using wavelet function [29, 30]. Thus, it leads to high frequency resolution in low frequencies and high time resolution in high frequencies. This multi-resolution analysis method is frequently used for the analysis of non-stationary signals due to its ability to obtain transition in both time and frequency domains. DWT is more advantageous than other transformation methods (e.g., Fast Fourier Transform (FFT)) in its ability to identify trends, breakdown points, and impairment in signals. Bartuzi and Roman-Liu show that the wavelet transform parameters might be better at evaluating MF than parameters of FFT for low levels of loads [31].

EMG signals are complex in nature and methods of collection data are nonlinear and disordered. Consequently, existing studies have applied various nonlinear tools for evaluating MF. As a result, applied methods afforded extra information about MF [32]. Webber et al. established that when MF occurs during isometric contraction in the BB muscle, nonlinear methods detect greater changes compared with MDF [33].

According to the literature, ApEn has been applied in numerous medical fields such as electroencephalography of psychiatric diseases, electrocardiography, respiratory system, and clinical endocrinology [34, 35, 36]. Pincus was the founder of ApEn, which is based on entropy theory [7]. In our literature review there was research of analysing EMG signals in which data are studied before, during, and after isometric muscle contraction. Ahmad and Chapell found that there was a clear decrease in ApEn value from the starting phase until the end phase [37].

CHAPTER 3

MATERIAL AND METHOD

3.1 PROCEDURE OF RECORDING EMG SIGNALS

The purpose of this thesis is to analyse MF during isometric contractions using surface EMG. For this aim, a group of 30 young volunteers (15 females, 15 males) participated in our study. They were all healthy people without any history of previous injury, metabolic, or muscular disorders. The BB and TB muscles were chosen for the test. These muscles are antagonists to each other, so they move in opposite directions. For instance, during the flexion movement done by the arm, while the BB muscle contracts the TB as the antagonist extends. Similarly, when the BB extends, the TB contracts [38].

In literature there are some features to evaluate MF, such as increasing amplitude in the time domain and transition from high frequency to low frequency in the frequency domain. MF was evaluated with these features that can be computed from EMG signals. But these parameters might not be enough to detect MF in its early stages and to evaluate quantitatively. Therefore, in our research we try to find nonlinear features using ApEn. First of all we divide our original signal using DWT for noise elimination and to get a sub-version, and then we compute the ApEn values of each approximation coefficient and detail coefficients. Finally, in order to evaluate the results scientifically a statistical analysis is done.

The experimental EMG data were obtained at Fatih University in Istanbul. EMG recordings were performed by Kezban Coşkun who has already accomplished her MSc thesis. The complete dataset consisted of signals of isometric contraction. In order to record EMG signals, the bioPlux version 1.2 research device was used (Figure 3.1) (Plux, Portugal).

Figure 3.1 bioPlux device

After ethical approval was received from Fatih University, EMG signals were obtained from the 30 healthy subjects' BB and TB muscles in an isometric constant force experiment. The female participants were asked to hold a 2.5 kg dumbbell and male participants to hold a 5 kg dumbbell. During the isometric contractions, EMG signals were recorded instantaneously from the BB and TB muscles [39]. The specific information about recording channels and experimental details are given in Table 3.2.

Table 3.1 Data Channels.

Channel	**Data**
1	Biceps Brachii EMG
2	Triceps Brachii EMG

Table 3.2 Specifications of EMG and volunteers.

Name	**Value**
Muscle Type	Biceps brachii and triceps brachii
Frequency	1000 Hz
Type of Contration	Isometric
Dumbbell Weight	Female (2,5 kg) - Male (5kg)
Number of participants	30 (15 females and 15 males)
Age	Female = 25.5 ± 1.96, Male = 23.86 ± 3.5
Weight	Female = 62.8 ± 9.94 kg, Male = 75.9 ± 11.26 kg
Height	Female = 1.66 ± 0.06 m, Male = 1.76 ± 0.06 m

In our experiments isometric contractions were analysed. During the isometric muscle contraction, the length of the muscle remains stable but the muscle tone is changed.

At the beginning of the test, the exercise and its purposes were expressed clearly to the volunteers. Excluding during the arm exercise, the volunteers were asked to keep their body as stable as possible as was wanted. Initially the related regions were cleansed with medical supplies in order to remove sediment and the dead layer of skin. Then EMG electrodes were placed on the muscle bundles. Silver-surface, bipolar, 4 mm-radius surface electrodes were placed on the bundles of muscles that were located by testing manually.

For the isometric contraction experiment, female volunteers were asked to hold a 2.5 kg dumbbell while their arm was open at a 90° angle for three minutes, and male volunteers were asked to hold a 5 kg dumbbell with their non-dominant arm.

3.2 DISCRETE WAVELET TRANSFORM

DWT analysis simultaneously shows information in discrete - time and frequency domain of a signal. Thus, it leads to high frequency resolution and low time resolution in low frequencies, and high time resolution and low time resolution in high frequencies. This analysis method is frequently used for the analysis of non-stationary signals. DWT is more advantageous than other transformation methods (e.g., FFT) to identify trends, breakdown points, and impairment in signals [31].

Mallat states that decomposing a discrete signal of $\chi\,[n]$ is possible [40]. So, DWT of a signal $\chi[n]$ is calculated by passing through a series of low pass (LP) and high pass (HP) filters. As a result we get the first Approximation Coefficients and Detail Coefficients from LP and HP filters, respectively, as shown in Figure 3.4. The approximation is a high frequency component whereas detail is a low frequency component of the signal. Then the first level of approximation and detail coefficients pass through the same steps to get second coefficients. This procedure continues for all levels, and in each of them frequency resolution is doubled and time resolution is halved.

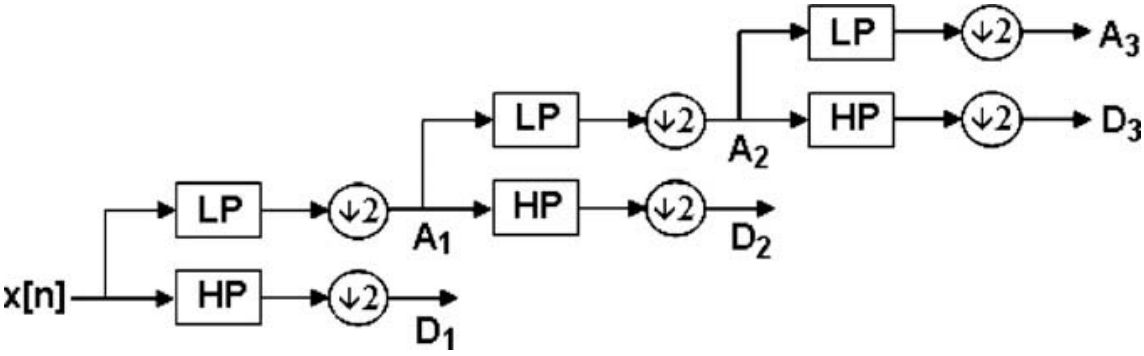

Figure 3. 4 Wavelet Tree Decomposition Structure [41]

Thus, mathematically DWT is calculated by this equation ;

$$\mathrm{DWT}(j,k) = \frac{1}{\sqrt{|2^j|}} \int_{-\infty}^{\infty} x(t)\psi\left(\frac{t-2^j k}{2^j}\right) dt \quad (3.1)$$

In this study we used the DWT method since it has been successful in analysing non-stationary signals, such as EMG [42]. Proper selection of the number of decomposition levels and suitable wavelet function are important for EMG signal analysis. We used Daubechies' wavelet decomposition with order 3, since many studies mention the performance of other levels of wavelet decompositions and level 3 is not common in the existing research [43, 44].

3.3 APPROXIMATE ENTROPY

ApEn is a non-linear measurement tool that was initially proposed by Pincus to fulfil requirements of signal complexity. It is based on a logarithmic likelihood that calculates repetitions of patterns of length m that are close within a defined r that will remain close to patterns of length $(m+1)$. ApEn takes into account the temporal order, which makes it more suitable to represent the points of time series and therefore is a preferred measure of regularity. The development of ApEn overcame the drawbacks of previously used tools in quantifying signal complexity such as having a measure to handle noise successfully and being applicable for small data samples and other model constraints [45, 46].

The main parameters of ApEn are data length (N), embedded dimension (m), time delay (t), and tolerance width (r).

In practice, we implement the following formula for ApEn for fixed m, r, and τ:

$$\mathrm{ApEn}(m, r, \tau, N) = \Phi^m(r) - \Phi^{m+1}(r) \quad (3.2)$$

3.4 STUDENT T-TEST

The t-test is used to compare two arrays of measurable data when samples are collected differently from one another. The t test can be implemented having the mean

value, standard deviation, and size of the array. The impact of the student's t-test is to realise that if there is a significant difference between the two arrays then the test can support a hypothesis [47].

CHAPTER 4

RESULTS AND DISCUSSION

In this thesis, raw EMG signals were analysed using DWT, in which Daubechies' wavelet was used at the third level. As such, one approximation coefficient at the third level (A3) and three detail coefficients (D3, D2, D1) were computed. As a result, for one EMG signal we get four subparts: A3, D3, D2, and D1. For all coefficients we received different results as shown in the plot diagram in Figure 4.1.

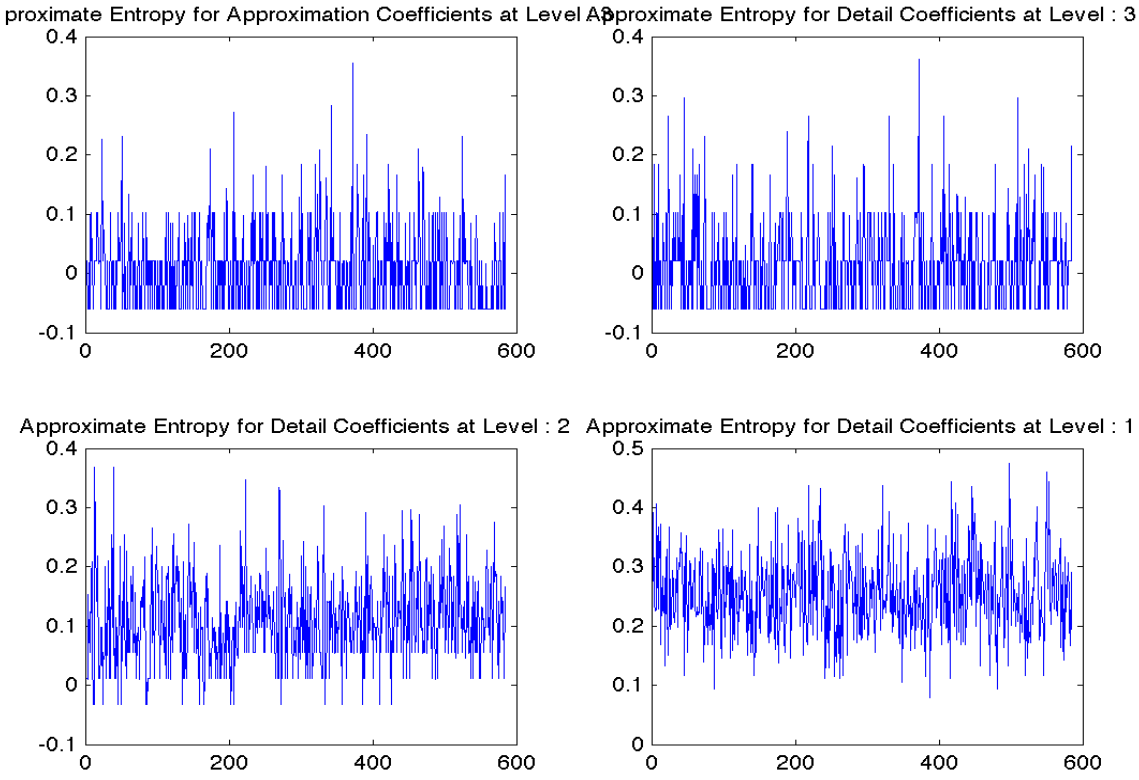

Figure 4.1 Decomposition of EMG with db3.

DWT has been used by different researchers and with different mother wavelets, such as Daubechies' db2, db3, Sym 4, and Sym5 [48]. Because of its advantages over FFT, as managing stronger non-stationarities which were observed in the EMG signals from an isotonic muscle contraction. Among the wavelets we chose Daubechies' db3 because in the literature there are a lot of successful researches for analysing EMG with db3 [49].

A clear and generally accepted description of fatigue is essential to ensure that researchers get comparable results; however, up to the present time, most research has only identified the non-fatigue and fatigue phases of muscles [50]. Other characteristics of MF research are central and peripheral mechanisms of fatigue, recommending that fatigue is not a particular state, but relatively contains different components that lead to fatigue. Hence, Al-Mulla et al. have classified another phase of fatigue, called Transition-to-Fatigue, which is in between non-fatigue and complete fatigue [13]. Based on Al-Mulla et al.'s work, we computed each coefficient's ApEn values in which each ApEn array contained a sample size of 1,125. We divided the arrays into three segments, and mean and standard deviation values of each segment were calculated. Then, we applied the t-test in order to find any statistical significance. In the literature of analysing EMG during and after isometric muscle contraction, Ahmad and Chapell found that there was a clear decrease in ApEn value from the starting phase until the end phase [37]. However, in our results ApEn values increased from the first segment until the third segment.

As a measure of entropy, ApEn can be computed using short and noisy experimental data sets, irrespective of the presence of any nonlinear properties. In this study, we found statistically significant changes in ApEn during the different stages of MF in healthy subjects, with lowest values during the last segment and highest values during the first segment.

Among our four data sets Approximate Entropy for Approximation Entropy Coefficients at level 3, Approximate Entropy for Detail Coefficients at level 3, Approximate Entropy for Detail Coefficients at level 2, Approximate Entropy for Detail Coefficients at level 1, that referrers to AA3, AD3, AD2 and AD1 in the tables respectively.

AA3 showed the best statistical difference for male volunteers that is 0.0088 and 0.0214 for female volunteers.

Table 4.1 Mean value of each segments' ApEn for Approximation Coefficients at Level 3 of BB in males.

EMG Signals of BB of male volunteers			
Patient No	Mean of **first** Segment	Mean of **second** Segment	Mean of l**ast** Segment
1	-0.0199	0.021	0.0125
2	-0.0199	0.021	-0.0199
3	-0.0199	0.0125	0.0533
4	-0.0607	0.0771	0.021
5	0.021	0.021	0.1407
6	-0.0199	-0.0199	0.021
7	-0.0607	0.021	0.1758
8	0.021	0.1025	0.2099
9	-0.0199	0.1046	0.021
10	-0.0607	0.0533	-0.0199
11	-0.0199	0.0105	0.0173
12	0.083	-0.0199	0.1468
13	-0.0607	-0.0199	0.1
14	0.0941	0.0617	-0.0199
15	-0.0607	0.0125	-0.0607
MEAN± SD	-0.0136 0.0498	0.0306 0.0409	0.0533 0.0816

Table 4.2 Results of the statistical analysis of the AA3 for segment comparison

FirstSegment- **Last**Segment	**p = 0.0088**

According to the results of mean values and t-test as shown in table 4.3, 4.4, 4.5, 4,6, 4.7 and table 4.8 respectively, p value showed a larger result than 0.05, so detail coefficients at each level are not statistically significant.

Table 4.3 Mean Value of each segments' ApEn for Detail Coefficients at Level 3 of BB in males.

EMG Signals of BB of male volunteers			
Patient No	Mean of **first** Segment	Mean of **second** Segment	Mean of **last** Segment
1	0.0592	-0.0199	0.021
2	0.1841	0.0592	-0.0607
3	0.1	0.0507	0.1
4	0.0533	0.021	-0.0199
5	0.1025	0.0617	-0.0309
6	0.0617	-0.0607	0.0617
7	-0.0607	0.021	0.2612
8	0.0915	0.0941	0.0742
9	-0.0224	0.0184	0.021
10	0.021	0.1348	0.0617
11	0.021	0.0617	0.0617
12	-0.0199	-0.0199	0.1025
13	-0.0199	-0.0199	0.1587
14	0.021	-0.0607	-0.0607
15	0.1179	-0.0199	-0.0199
MEAN±SD	0.0474 0.0652	0.0215 0.0561	0.0489 0.0867

Table 4.4 Statistical analysis of the AD3 for segment comparison of BB in males.

FirstSegment- **Last**Segment	**p=0.9684**

Table 4.5 Mean Value of each segments' ApEn for Detail Coefficients at Level 2 of BB in males.

EMG Signals of BB of male volunteers			
Patient No	Mean of **first** Segment	Mean of **second** Segment	Mean of **last** Segment
1	0.2059	0.1109	0.1409
2	0.0109	0.0938	0.0983
3	0.1057	0.1446	0.1326
4	0.1855	0.0759	0.0766
5	0.07	0.0834	0.1581
6	0.1211	0.1651	0.0505
7	0.2145	0.1516	0.2772
8	0.1917	0.1662	0.2074
9	0.0333	0.1416	0.0116
10	0.1147	0.186	0.1109
11	0.0491	0.0549	0.1281
12	0.0326	0.1224	0.0766
13	0.0669	0.0542	0.1979
14	0.1453	0.1199	0.1064
15	0.0938	0.0766	0.0549
MEAN±SD	0.1094 0.0671	0.1165 0.0422	0.1219 0.0686

Table 4.6 Statistical analysis of the AD2 for segment comparison of BB in males.

FirstSegment- **Last**Segment P - Value	0.4991

Table 4.7 Mean Value of each segments' ApEn for Detail Coefficients at Level 1 of BB in males.

EMG Signals of BB of male volunteers			
Patient No	Mean of **first** Segment	Mean of **second** Segment	Mean of **last** Segment
1	0.3507	0.2911	0.2606
2	0.2107	0.2776	0.2445
3	0.2137	0.3371	0.397
4	0.3104	0.3192	0.3509
5	0.3333	0.2702	0.2689
6	0.2763	0.2524	0.3802
7	0.2681	0.3497	0.4119
8	0.2915	0.3032	0.3192
9	0.268	0.2179	0.2071
10	0.2741	0.2841	0.3188
11	0.2156	0.3167	0.2353
12	0.3185	0.1835	0.2783
13	0.2495	0.3592	0.3436
14	0.275	0.275	0.2492
15	0.2522	0.2007	0.2424
MEAN±SD	0.2738 0.0425	0.2825 0.0523	0.3005 0.0646

Table 4.8 Statistical analysis of the AD1 for segment comparison of BB in males.

FirstSegment- **Last**Segment	**p=0.2120**

Table 4.9 Mean Value of each segments' ApEn for Approximation Coefficients at Level 3 of BB in females.

EMG Signals of BB of female volunteers			
Patient No	Mean of **first** Segment	Mean of **second** Segment	Mean of **last** Segment
1	-0.0607	-0.0607	-0.0199
2	-0.0607	-0.0607	0.021
3	-0.0607	-0.0199	0.021
4	0.021	-0.0199	-0.0199
5	0.021	0.0533	0.021
6	-0.0607	-0.0199	-0.0607
7	-0.0199	0.0507	0.1
8	-0.0607	-0.0199	-0.0607
9	-0.0199	-0.0199	-0.0199
10	-0.0607	0.0533	-0.0199
11	0.021	0.021	0.021
12	-0.0199	0.021	0.021
13	-0.0199	0.0959	0.2487
14	0.021	0.0125	0.0861
15	-0.0607	0.0974	-0.0199
Mean±SD	-0.0281 0.0352	0.0123 0.05	0.0213 0.0775

Table 4.10 Statistical analysis of the AA3 for segment comparison of BB in females.

First Segment - Last Segment	**p=0.0214**

When we did the calculations for female data also we got the same results as male volunteers data. According to the results of mean value and t-test as shown in table 4.11, 4.12, 4.13, 4,14, 4.15 and table 4.16 p value showed a larger result than 0.05, so detail coefficients at each level are not statistically significant.

Table 4.11 Mean Value of each segments' ApEn for Detail Coefficients at Level 3 of BB in females.

EMG Signals of BB of female volunteers			
Patient No	Mean of **first** Segment	Mean of **second** Segment	Mean of **last** Segment
1	-0.0199	0.0617	0.0617
2	-0.0199	0.021	0.0941
3	-0.0199	0.0533	-0.0199
4	0.021	0.0125	-0.0607
5	0.021	0.0184	0.5105
6	-0.0199	0.021	0.021
7	-0.0199	0.021	-0.0199
8	0.0617	-0.0199	0.0617
9	-0.0607	0.0184	-0.0199
10	-0.0199	0.1264	-0.0607
11	-0.0607	-0.0199	-0.0199
12	0.0125	0.0507	-0.0199
13	-0.0224	0.0184	0.021
14	0.0507	0.0617	0.1139
15	-0.0607	0.021	0.021
Mean±SD	-0.0105 0.0375	0.0311 0.0362	0.0456 0.1388

Table 4.12 Statistical analysis of the AD3 for segment comparison of BB in females.

First Segment - Last Segment	**p=0.1189**

Table 4.13 Mean Value of each segments' ApEn for Detail Coefficients at Level 2 of BB in females.

EMG Signals of BB of female volunteers			
Patient No	Mean of **first** Segment	Mean of **second** Segment	Mean of **last** Segment
1	0.0983	0.0983	0.2062
2	0.1281	0.1154	0.1669
3	0.114	0.17	0.2129
4	0.0549	0.0542	0.1199
5	0.1274	0.1543	0.1371
6	0.1199	0.1199	0.0983
7	0.1543	0.1357	-0.0101
8	0.0766	0.1147	0.1271
9	0.1491	0.0938	0.1057
10	0.1267	0.0983	0.1527
11	0.0549	0.2185	0.0721
12	0.1446	0.1498	0.0617
13	0.0549	0.1842	0.0549
14	0.1439	0.1714	0.1512
15	0.1752	0.1714	0.152
Mean±SD	0.1149 0.0389	0.1149 0.043	0.1149 0.0593

Table 4.14 Statistical analysis of the AD2 for segment comparison of BB in females.

First Segment - Last Segment	**p=0.7529**

Table 4.15 Mean Value of each segments' ApEn for Detail Coefficients at Level 1 of BB in females.

EMG Signals of BB of female volunteers			
Patient No	Mean of **first** Segment	Mean of **second** Segment	Mean of **last** Segment
1	0.2899	0.2411	0.2874
2	0.168	0.2317	0.19
3	0.2462	0.22	0.3121
4	0.1961	0.2289	0.2325
5	0.3057	0.2295	0.2699
6	0.2753	0.2746	0.2753
7	0.3163	0.33	0.2714
8	0.2315	0.3447	0.2687
9	0.2416	0.238	0.3231
10	0.223	0.168	0.2888
11	0.2651	0.2253	0.2534
12	0.2738	0.2647	0.1483
13	0.1995	0.2158	0.2928
14	0.2936	0.2771	0.3405
15	0.2191	0.1622	0.1466
Mean±SD	0.2497 0.0437	0.2434 0.0499	0.2601 0.0582

Table 4.16 Statistical analysis of the AD1 for segment comparison of BB in females.

First Segment - Last Segment	**p=0.5202**

The same operations are repeated for female isometric data of TB muscle. However, different results are obtained. When we look at table 4.17, 4.18, 4.19, 4.20 and table 4.21 we see that unlike BB muscle data the p value of TB in each coefficient is higher than 0.05 this means there are not any significant difference.

Table 4.17 Mean Value of each segments' ApEn for Approximation Coefficients at Level 3 of TB in females.

EMG Signals of TB of female volunteers			
Patient No	Mean of **first** Segment	Mean of **second** Segment	Mean of **last** Segment
1	-0.0199	0.0209	-0.0606
2	0.0209	0.218	-0.0199
3	-0.0199	0.0745	0.0209
4	-0.0199	-0.0199	0.0209
5	-0.0199	-0.0199	-0.0224
6	0.0099	-0.0199	0.0125
7	-0.0199	-0.0606	0.0184
8	0.0617	-0.0199	0.0184
9	0.0617	-0.0199	-0.0199
10	0.0532	-0.0199	0.0158
11	0.0184	-0.0199	-0.0199
12	-0.0199	-0.0199	0.1535
13	0.0209	0.0209	0.0209
14	0.0617	0.0617	0.1179
15	0.1034	0.0209	0.0855
Mean±SD	0.0871 0.0418	0.0617 0.0209	0.1034 0.0125

Table 4.18 Statistical analysis of the AA3 for segment comparison of TB in females.

First Segment - Last Segmet	**p= 0.8380**

Table 4.19 Statistical analysis of the AD3 for segment comparison of TB in females.

First Segment - Last Segment	**p= 0.5401**

Table 4.20 Statistical analysis of the AD2 for segment comparison of TB in females.

First Segment - Last Segment	**p= 0.8642**

Table 4.21 Statistical analysis of the AD1 for segment comparison of TB in females.

First Segment - Last Segment	**p= 0.3245**

Finally we can say literature is poor on application of DWT and ApEn for evaluation of MF. Therefore the performance of the proposed method is not compared to previous studies since we could not classify similar studies but came up with a new try of methods for evaluation of MF in isometric muscle contractions.

CHAPTER 5

CONCLUSION

To prevent occupational accidents and to increase work and sport efficiency, scientists try to measure MF. For the purpose of early detection of MF, various analysing tools have been used since it affects performance and might cause injury. Thus, creating a computerised system to detect MF in an early phase by warning the person is essential in order to increase human performance during daily work, sports, and other manual activities. The system can also be applied in occupational health and ergonomics, especially where there is the risk of occupation disorders to the muscular system. In the literature, few studies concentrate on the clinical side and the parameters are not enough to detect MF in its early phase and to evaluate it quantitatively. Therefore, in our research we tried to find a nonlinear feature using ApEn and get quantitative data.

In this study, a new pattern is presented for evaluating MF by recording EMG signals that were collected from the BB and TB of 30 volunteers (15 males and 15 females). First of all, original EMG signals were decomposed using DWT for noise elimination and to get sub-versions. There are different types of wavelet functions, which give the appropriate results in the time and frequency domains. In this paper we have used Daubechies' family with db3 wavelet function. Then ApEn was computed on each value of approximation and detail coefficients. To analyse MF, the outputs of approximation coefficients and detail coefficients are separated into three equal segments, and the mean of each segment is calculated. Finally, the t-test was applied to find out if there were any statistical differences between the first segment that is the beginning of the signal and the third segment in which fatigue is seen.

The result shows that fatigue happens during isometric contractions. Among our four data sets, only AA3 showed the best statistical difference in which the p value is 0.0088 for male BB muscle signals and 0.0214 for female BB muscle signals. However, the results of the TB muscle signals are not statistically significant since the p value of all coefficients is greater than 0.05.

In the present work, the proposed ApEn was only applied to an EMG signal during isometric contractions. ApEn measurements in EMG might be clinically useful in the evaluation of fatigue stages and to calculate muscle activity. However, the fatigue analysis of the EMG signals noticed during isotonic contractions has been useful in a number of applications of daily activities such as sports medicine ergonomics and rehabilitation, so it is important to consider isotonic contractions. Also, it is vital to analyse longer fatigue situations in order to get applicable results since our study is for short-term fatigue. Further study is needed to explain the usefulness of the ApEn in relation to the automatic diagnosis of MF.

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