UNIVERSITY OF ÇUKUROVA
INSTITUTE OF NATURAL AND APPLIED SCIENCES

MSc THESIS

Rouhollah DIZBARI GHARAJEHDAGHI

CLASSIFICATION OF HAND MOVEMENTS WITH ELECTROMYOGRAM SIGNALS OBTAINED FROM ARM MUSCLES: GENERATING CONTROL SIGNALS FOR HAND PROSTHESIS

DEPARTMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

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We certify that the thesis titled above was reviewed and approved for the award of degree of the Master of Science by the board of jury on

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ABSTRACT

MSc THESIS

CLASSIFICATION OF HAND MOVEMENTS WITH ELECTROMYOGRAM SIGNALS OBTAINED FROM ARM MUSCLES: GENERATING CONTROL SIGNALS FOR HAND PROSTHESIS

Rouhollah DIZBARI GHARAJEHDAGHI

CUKUROVA UNIVERSITY
INSTUTE OF NATURAL AND APPLIED SCIENCES
DEPATMENT OF ELECTRICAL AND ELECTRONICS ENGINEERING

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Electromyography (EMG) signals are outcomes of muscle activities. An EMG signal is read by prickling needle electrode to the muscle or is read non-invasively from the skin surface by placing electrodes on the skin over the target muscle (surface EMG - SEMG). Activities on the biological signals during the times helped to find new methods and technics to both how to use EMG signals and modeling of hand movements. In this study we aim to generate control signals from SEMGs measured from four hand muscles; Extensor carpi radialis, Palmaris longus, Pronator teres, Flexor digitorum superficialis to navigate a prosthesis hand. The SEMGs for five hand movements; finger flexion, wrist flexion, wrist extension, pronation, supination have been acquired. From each muscle (channel), the mean power, peak value of the envelope, the mean frequency of discrete Fourier transform and the estimated frequency by signal subspace method are extracted as features. The different combination of these features have been classified with three different classifiers; linear Bayes classifier, Fisher' s linear discriminant and support vector machine. The classifications have been done for three groups; inter-subject (training and testing data are from the same subject), intra-subject (training and testing data are from different subject), classification of right hand data from the left hand data and vice versa and the performances of the feature combinations and the classifiers have been reported. The highest average performance for inter-subject classification and intra-subject classification have been 99.61% with linear Bayes classifier and 71.8% with linear SVM repectively. The success of the left hand versus right hand (and right versus left) classification with SVM classifier has been at least 36.7% and at most 82.7%.

Keywords: Prosthetic hand, EMG, linear Bayes classifier, Fisher' s LDA,SVM

ÖZ

YÜKSEK LİSANS TEZİ

KOL KASLARINDAN OKUNAN ELEKTROMIOGRAM İŞARETLERİNDEN EL HAREKETLERİNİN SINIFLANDIRILMASI: PROTEZ EL İÇİN KONTROL İŞARETLERİ OLUŞTURMA

Rouhollah DIZBARI GHARAJEHDAGHI

ÇUKUROVA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ
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: Doç. Dr. Mustafa GÜVEN
: Yrd.Doç. Dr. Murat AKSOY

Elektromiyografi (EMG) işaretleri kas aktivitelerinin bir sonucudur. Bir EMG işareti kasa iğne elektrodu batırarak yada hedef kaslara karşılık gelen cilt yüzeyine elektrot yerleştirilerek harici olarak (yüzey EMG - SEMG) okunur. Biyolojik sinyeller üzerinde calışmalar, EMG işaretlerinin yorumlanması ve el hereketlerinin modellemeleri ve sınıflamaları için yeni yöntemler bulmasını sağlamıştır. Bu çalışmada dört kastan; Extensor carpi radialis, Palmaris longus, Pronator teres, Flexor digitorum superficialis okunan SEMG işaretlerininden bir protez eli yönlendirecek kontrol işaretleri oluşturmak amaçlanmaktadır. SEMG işaretleri beş el hereketi; parmak bükme, bilekten içe bükme, bilekten dışa bikme, aşağı bükme ve yukarı bükme, için alınmıştır. Her kastan (kanaldan); ortalama güç, zarfın tepe değeri, Fourier dönüşümünün ortalama frekansı ve sinyal altuzay medodu ile kestirilmiş frekans özellikleri elde edilmiştir. Bu özelliklerin farklı kombinasyonları üç farklı sınıflayıcı; doğrusal Bayes sınıflayıcı, Fisher doğrusal ayrıştırıcı ve destek vektör aracı, kullanılarak sınıflandırılmıştır. Sınıflamalar üç grup için yapılmıştır; denek – içi (eğitim ve test verileri aynı denekten), denekler-arası (eğitim ve test verileri farklı denekten), sağ el verisinin sol verisinden tahmini yada tersi ve özellik kombinasyonlarının ve sınıflayıcıların performansları rapor edilmiştir.

Denek-içi en yüksek ortalama başarı doğrusal Bayes sınıflayıcısı ile %99.61 ve denekler-arası en yüksek ortalama başarı doğrusal SVM sınıflatıcı ile %71.8 olmuştur. SVM sınıflayıcı ile sol ele karşı sağ el (yada sağ ele karşı sol el) sınıflama başarısı en az %36.7, en çok %82.7 dir.

Anahtar Kelimeler : Protez el, EMG, doğrusal Bayes sınıflayıcı, Fisher doğrusal ayrıştırıcı, destek vektör aracı

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LIST OF ABBREVIATIONS

EMG	: Electromyography
SEMG	: Surface electromyography
PCA	: Principal component analysis
ICA	: Independent component analysis
LM	: Levenberg marquardt
VLR	: Variable rate
AR	: Autoregressive
DCS	: Dynamic classifier selection
ANN	: Artificial neural network
BP	: Back propagation
SVM	: Support vector machine
LDA	: Linear discriminant analysis
MLP	: Multilayer perceptron
CKLM	: Cascaded kernel learning machine
MUAP	: Motor unit action potential
mV	: Mili volt
D/C	: Direct current
A/C	: Alternating current
FIR	: Finite impulse response
rad/s	: Radian per second
ω_0	: Cut-off frequency
dB	: Decibel
Hz	: Hertz
PSD	: Power spectral density
TFR	: Time-frequency representations
STFT	: Short time Fourier transform
DWT	: Discrete wavelet transform
WPT	: Wavelet packet transform
CWT	: Continuous wavelet transform

nF	: Nanofarad
$X_+(n)$	: Pre-envelope of x(n)
k_a	: Frequency index
$\omega(n)$	: Hamming window
MUSIC	: Multiple signal classification
R_x	: Autocorrelation matrix
v_i	: Noise eigenvectors
w	: Weight vector
b	: Parameter of the hyperplane
$\varphi(x)$	: feature space transformation
S_w	: Within-class scatter
S_b	: between-class scatter
P	: Peak value function
$\hat{X}^2$	: Mean power function
$\hat{f}$	: Mean frequency function
fs	: Frequency estimation function

1. INTRODUCTION

1.1. Introduction and motivation

The majority of upper limb amputations are related to injuries because of accidents, wars, and natural disasters and little are related to vascular diseases and congenital defects. Loss of hand may give negative consequences on the individual's quality of life and specifically on human ability to fully participate in many work environments, those that involve hands. Although the hand is missing, remain can be flexed. This muscle activity can be read from the skin surface as electromyography (EMG) signals by placing electrodes on the forearm (SEMG). Activities on the biological signals during the times helped to find new methods and technics to both how to use electromyography (EMG) signals and modeling of hand movements. It opened the door to work and life opportunities previously unavailable to the upper limb amputees (Al-Assaf, 2006).

A successful myoelectric control system is defined by three subjects are acceptable: accurate, intuitive control, and acceptable response time; the probability of rejection of prosthesis by the user is strongly influenced by these factors. The control system must obviously aim to function such that the prosthesis performs the task desired by the user with nearly 100% accuracy. A measure of intuitive control has not yet been successfully quantified, though more natural control has been achieved with user-specific training on control systems (Al-Assaf, 2006), (Zardoshti-Kermani, Wheeler, Badie, & Hashemi, 1995). The response time of a myoelectric control system should not be perceptible by the user (Englehart, Hudgins, & Chan, 2003).

Upper limb amputees have two different options for prosthetic:

1. Passive prostheses that do not actively grasp but have an excellent cosmetic appearance that they can look incredibly natural. They present only few user concerns.

2. Active prostheses (or functional prosthetic), which allow the user to hold and manipulate objects but with lower attractive appearance. Functional prostheses can help people perform different activities of daily living (Kejlaa, 1993).

The main goal of our research is to employ EMG signals to successfully identify which type of hand movements is done. The identification of the movement type or the features to identify the movement type can be used to generate control signals for a robotic arm by considering this goal the algorithm is realized with a minimum run time and maximum accuracy as possible.

1.2. Previous Studies

Myoelectric control system studies first time is done at Munich University by a physics faculty student, Reinhold Reiter. In 1945, his article " Design of a prosthetic arm for factories amputated workers" was published in the German medical journal. And the prototype of his work was demonstrated at the Honnover export fair. The aim goal of Reiter was, to control of wooden hand by a solenoid, with myoelectric signals that achieved from muscle contractions. Using two different contraction rhythm, provided the open and close hand controls. Reiter' s ideas were used in many countries independent from each other. The researchers, tried to resolve the missing sides of Reiter' s studies (Muzumdar, 2004).

With the development of signal processing techniques and artificial intelligence techniques, deficiencies in the first studies were resolved and prosthetic limbs were developed.

For an acceptable modeling, the physiology of the human body has to be known too. The prosthetic artificial hands can be divided into three parts. The first part is the mechanical solutions for operating with sufficient freedom in the hands. The second is the electronic circuits to ensure capableness and speed motion in mechanical part. The third is to obtain crude EMG signals and use them. Many studies have been done about the prosthetic artificial hands in recent years. Belo sum of them are summarized:

Shyu obtained SEMG signals from the hands of 9 males and 2 females and used wavelet transform and artificial neural network for classification. Shyu used principal component analysis (PCA) and independent component analysis (ICA) for lowering the number of channels from 7 to 4. He found that both ICA and PCA increase the number of training epochs of the artificial neural network and PCA reduces the size of the neural network by more than 70% (Du, Hu, & Shyu, 2004).

Mahdi and his friends from Sharif University of technology, reduced the size of EMG signal by using principal component analysis (PCA) and employed Fuzzy classifier for classification. They used three types of SEMG features, namely time, time frequency and compound features. They obtained a high degree of correctness for recognizing each of the six selected movements of hand by using compound features. The proposed neuro-fuzzy system exhibited very good results as the minimum accuracy obtained by this system by using compound features was 90% (Table 1.1) (Khezri & Jahed, 2007).

Table 1.1. Comparing the effectiveness of feature type for recognizing EMGPatterns

Feature Types	Opening	Closing	Wrist Flexion	Wrist Extension	Pinch	Thumb Flexion
Time Domain	%90	%100	%88	%84	%84	%80
Time frequency Domain	%94	%98	%92	%92	%88	%84
Compound Features	%98	%100	%96	%98	%94	%90

Zhizeng and his friends obtained SEMG signals from forearm and used their power spectrum coefficients as features and they did classification with Bayesian statistical algorithm. The classification accuracy of their method was 84% (Zhi-zeng, Fei, & Ren-cheng, 2005).

Zhao from the Harbin Institute used Levenberg Marquardt (LM) and variable learning rate (VLR) based neural network with parametric Autoregressive (AR) and Wavelet parameter to discriminate the EMG patterns. They found that the experimental results showed that using wavelet parameter and VLR based neural network has high recognition ability and fast learning speed even for several samples of each motion. The minimum accuracy obtained of VLR network recognition ability by using AR model and Wavelet transform was 70% whereas it was 50% by using LM network recognition ability system (Zhao, Xie, Jiang, Cai, Liu, & Hirzinger, 2006).

Kurzynski and his friend used the coefficient of an autoregressive (AR) model to represent signal features by and applied the original multiclassifier system with a dynamic ensemble selection. The systems were developed to achieve the highest overall classification accuracies for demonstrating the potential of dynamic classifier selection (DCS) in recognition of EMG signals (Kurzynski, Woloszynski, & Wolczowski, 2010).

Ahsan and his friends described the process of detecting different predefined hand gestures (left, right, up, down) by using artificial neural network (ANN). They employed back-propagation (BP) network with Levenberg-Marquardt (L-M) training algorithm for the detection of gesture. Their experimental result showed that the L-M algorithm based neural network recognizes the desired motions efficiently and takes minimal computation time. They found that the designed ANN successfully classified the EMG signals from hand movements. The average success rate was 88.4%; whereas in a single trial the best overall performance found 89.2%. (Ahsan, Ibrahimy, & Khalifa, 2011).

A group in Marmara University, acquired SEMG signals with a home-made four channel SEMG amplifier. They filtered the recorded SEMG signals with a band pass filter. In the second step signal' s features extracted. They used features eight features extracted in time-domain and two features extracted from the frequency domain for classification of motions. They classified seven different motions by ANN and Gustafson Kessel algorithm. They also compared their classification performances. In order to test the classifiers, their training process was repeated 10 times. They found that ANN classifiers give better rates than the Fuzzy classifier and the network that has 20 hidden neurons show highest performance with 91.95% average classification rate against the others. They also found that with the using Diffusion map algorithm for dimension reduction for Gustafson Kessel algorithm, the average classification result is 81.48% (Table 1.2) (Marmara, Varol, & Yildiz, 2012).

Table 1.2. Classification rates of classifiers

Classifier	Max	Min	Average	Number of Hidden Neurons
ANN	%95.42	%85.71	%91.95	20
	%94.89	%83.45	%89.26	30
Diffusion Map Gustafson Kessel	%84.35	%78.62	%81.48	-

The support vector machines (SVM) have been widely used in classification of EMG signals (Oskoei and Huosheng 2008) (Yoshikawa, Mikawa and Tanaka 2006) (Yi-Hung Liu, Han-Pang Huang and Chang-Hsin Weng 2007) (Rekhi, et al. 2009). All of the implementations have reported accuracy rates above 90%; the highest rate is 96.76% (Yi-Hung Liu, Han-Pang Huang and Chang-Hsin Weng 2007).

Yoshikawa et al. (Yoshikawa, Mikawa and Tanaka 2006) proposed a real time hand motion estimation method using EMG signals. They placed four surface electrodes on a patient's forearm to recognize seven hand motions: at rest, opening of the hand, closing of the hand, pronation, supination as well as wrist flexion and extension (Personal-EMG, Oisaka Development Ltd.). In order to perform the classification they used an SVM. With the set of features, the classification rate ranged from approximately 87% to 92%.

Oskoei et al. (Oskoei and Huosheng 2008) compared the classification ability of SVMs with linear discriminant analysis (LDA) and multilayer perceptron (MLP) neural networks. This article described many interesting observations. One of the experiments tested the accuracy of classifications performed on different lengths of EMG data ranging from 50 to 500 ms. The performance of various features or sets of features was evaluated. The results of the research indicated that longer segments (200 ms) of raw EMG data produced better classification accuracy. The SVM based classifiers achieved the highest classification accuracy at 95.5%, with the LDA classifier performing at 94.5%. A two layer MLP performed with similar accuracy to the SVM and LDA, whereas a one layer MLP lost 6% in accuracy.

Rekhi et al. (Rekhi, et al. 2009) performed EMG classification using features determined by wavelet packet analysis. The singular value decomposition was also used to reduce the dimensionality of the coefficients produced by the wavelet packet analysis. This study attempts to classify six different hand motions similar to the previous articles and results in an accuracy rate of 96%.

Liu et al. (Yi-Hung Liu, Han-Pang Huang and Chang-Hsin Weng 2007) used a much more complex cascaded kernel learning machine (CKLM) which was composed of a generalized discriminant analysis algorithm and an SVM. It documents the superior performance of this classifier in comparison with other common neural networks including the k-nearest neighbor algorithm, MLP networks and SVMs. The cascaded kernel learning machine was able to achieve an accuracy of 93.54%.

2. BACKGROUND

2.1. Electromyogram (EMG)

Electromyography (EMG) measures and records the electrical activity of a muscle and represent the electrical activity generated when skeletal muscles are contracted after an action potential stimulated the muscle fibers. Namely, EMG measures the muscle fiber action potentials of a single (or more) motor unit, which are known as the motor unit action potentials (MUAPs) as shown n Figure(2.1).

EMG signals are commonly recorded in one of two methods: surface EMG (SEMG) and intramuscular EMG. Surface EMG, records EMG by using electrodes placed on the skin (Figure 2.2), which is more popular than intramuscular EMG (a needle electrode is inserted directly into the muscle) (Figure 2.3). In the intramuscular recordings, the effect of volume conductor is minimal. The signal is detected close to the source and consists of the activity of a few muscle fibers belonging to 10 to 15 motor units. The SEMG is non-invasive and can be conducted simply, with minimal risk to the subject. The detection volume of the surface electrodes is much larger than that on the intramuscular electrodes (Theis & Meyer, 2010), (Palaniappan, 2010), (Norali & Mat Som, 2009).

The EMG signal is normally a function of time and is describable in terms of its amplitude, frequency, and phase. The actual potential is about 100 mV but due to the layer of connective tissue and skin, the SEMG is a complex signal with much less amplitude (typically about 5 mV).

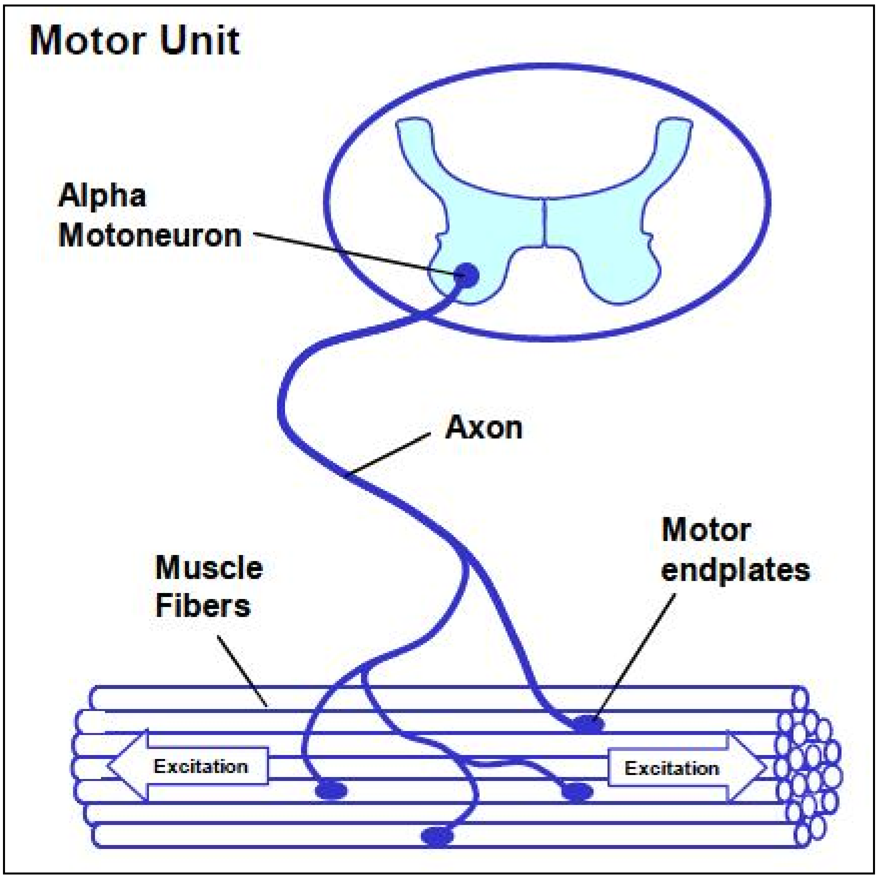

Figure 2. 1. Motor Unit (Konrad 2005)


Figure 2.2. A scene from SEMG recording from my hands

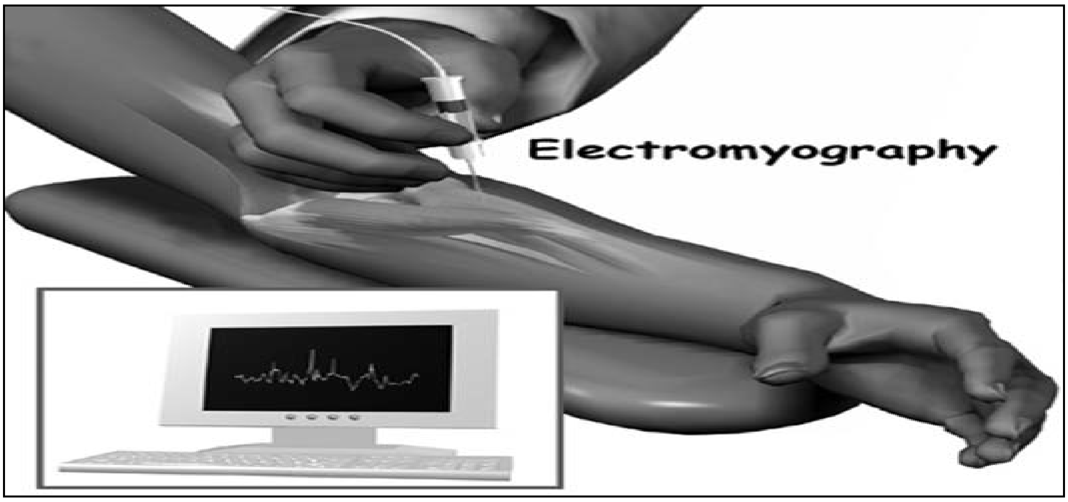

Figure 2.3. Intramuscular EMG

The typical benefits of EMG can be summarized as in the following:

- EMG allows to directly “ look” into the muscle
- It allows the measurement of muscular performance
- Helps in decision making both before/after surgery
- Documents treatment and training regimes
- Helps patients to “ find” and train their muscles
- Allows analysis to improve sports activities
- Detects muscle response in ergonomic studies

2.2. Structure ofthe muscles

EMG signal isa complicated signal, which is controlled by the nervous system and isdependent on the anatomical and physiological properties of muscles. A muscular organ is composed mainly of skeletal muscle tissue, nerves, and vascular and other connective tissue components. Skeletal muscle Consists of long, thin cells called fibers.Their length is between 10– 150 mm and their diameters are between 10– 100μm. Skeletal muscle is made up of tendons, which attach the muscle to the bones, and the muscle belly.The tendons are connective tissue that is formed at the end of the muscle fibers.Each individual muscle fiber contains thousands of small units called sarcomeres. Each sarcomere contains alternating rows of two proteins called actin and myosin. These two proteins actually work together to produce contractions, as they are arranged in filaments. The work that makes the muscle contract. The brain sends a signal to move. The myosin reaches out and attaches to and pulls on the action. This is what makes the muscle contract. When the actin and myosin release, the muscle relaxes back to its original length(Buurke, Harlaar, & Zilvold, 1998),(Cram, Kasman, & Holtz, 1998).

2.3. Types Of The Surface Electrodes

The surface electrode is an important component of the measurement system. The current in the body is carried by ions, whereas electrons are the carriers in the electrodes and its lead wires. Thus, the electrodes serve as a transducer to change an ionic current into an electronic current.

The choice of electrode material also is as important as the section of electrode size. The materials comprising the stimulation electrode should be both highly conductive and stable to electrolytic corrosion. Two types of surface electrodes are commonly in use:

1. Dry electrodes in direct contact with the skin.
2. Floating electrodes using an electrolytic gel as a chemical interface between the skin and the metallic part of the electrode (Windhorst and Johansson 1999), (Duchene and Gouble 1993), (Laferriere, Lemaire and Chan 2011).

2.4. Sources of Noise and Removal

EMG signal sometimes contains inevitable noise. For eliminating unwanted noises we must understand what the sources of noise are. Noise in EMG signal is categorized into the following types (Norali and Mat Som 2009), (Reaz, Hussain and Mohd-Yasin 2006):

1) Inherent noise in electronics equipment: All electronic equipment generates noise. This noise cannot be eliminated; using high quality electronic components can only reduce it.
2) Ambient noise: Electromagnetic radiation is the source of this kind of noise. The surfaces of our bodies are constantly inundated with electric-magnetic radiation and it is virtually impossible to avoid exposure to it on the surface of earth. The ambient noise may have an amplitude that is one to three orders of magnitude greater than the EMG signal.
3) Motion artifact: It could be caused by electrode moving on the skin surface and electrode wire movement that can be reduced by proper design of the electronic circuitry. Noise produce by motion artifact is in the range of 0 to 20 Hz and the best way to deal with this noise is using high-pass filter.
4) The inherent instability of signal: The amplitude of EMG is random in nature. EMG signal is affected by the firing rate of the motor units, which, in most conditions, fire in the frequency region of 0 to 20 Hz. This kind of noise is considered as unwanted and the removal of the noise is important.
5) Transducer Noise: Transducer Noise is generated at the electrode-skin junction. There are two types of noise sources that result from this transduction from an ionic to an electronic form:

   a) D/C (Direct Current) Voltage Potential: caused by differences in the impedance between the skin and the electrode sensor, and from oxidative and reductive chemical reactions taking place in the contact region between the electrode and the conductive gel (Gerdle, Karlsson and Day 1999).

   b) A/C (Alternating Current) Voltage Potential: generated by factors such as fluctuations in impedance between the conductive transducer and the skin. One effective method to decrease impedance effects is to use Ag-AgCl electrodes. This electrode consists of a silver metal surface plated with a thin layer of silver chloride material (Duchene and Gouble 1993).

3. MATERIAL AND METHOD

3.1. Block Diagram Of EMG Signal Process

In this study EMG signal obtained from the forearm, Then features are extracted for classifying.

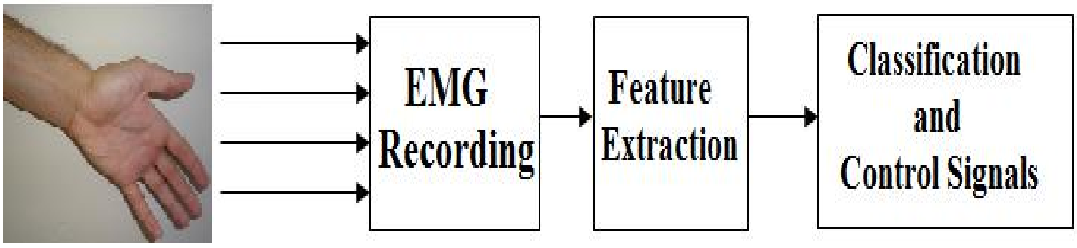

Figure 3.1. Block Diagram of EMG Signal Process

3.2. Hand Movements For EMG Recording

In this study we chose five hand movement; finger flexion, wrist flexion, wrist extension, pronation, supination as is seen in figure 3.2.

Figure 3.2. Hand movements

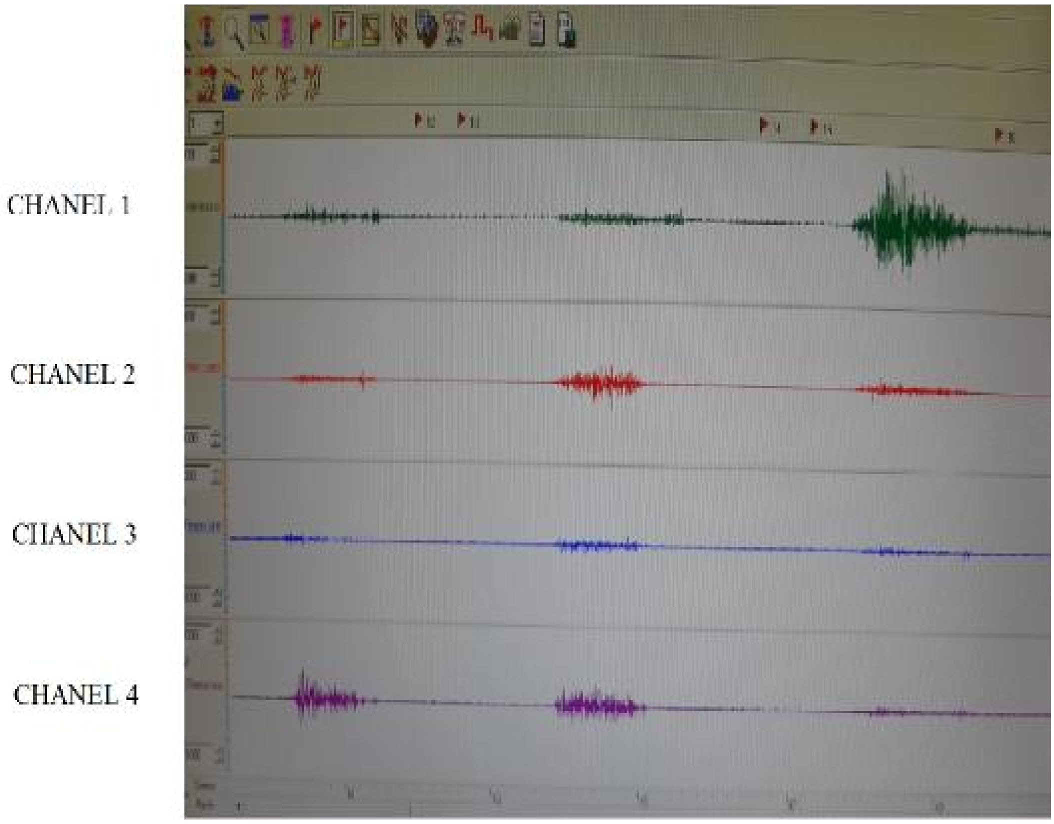

Figure 3.3. The EMG signals of hand movements

3.3. Chosen Muscle Groups

We used a four-channel EMG device for recording simultaneously four muscle groups. The chosen muscle group for recording are (Figure 3.4):

1. Extensor carpi radialis
2. Palmaris longus
3. Pronator teres
4. Flexor digitorum superficialis

Before recording we used muscle stimulator for correctly specifying muscles locations and placed electrodes on the specified locations(Figure 3.5).

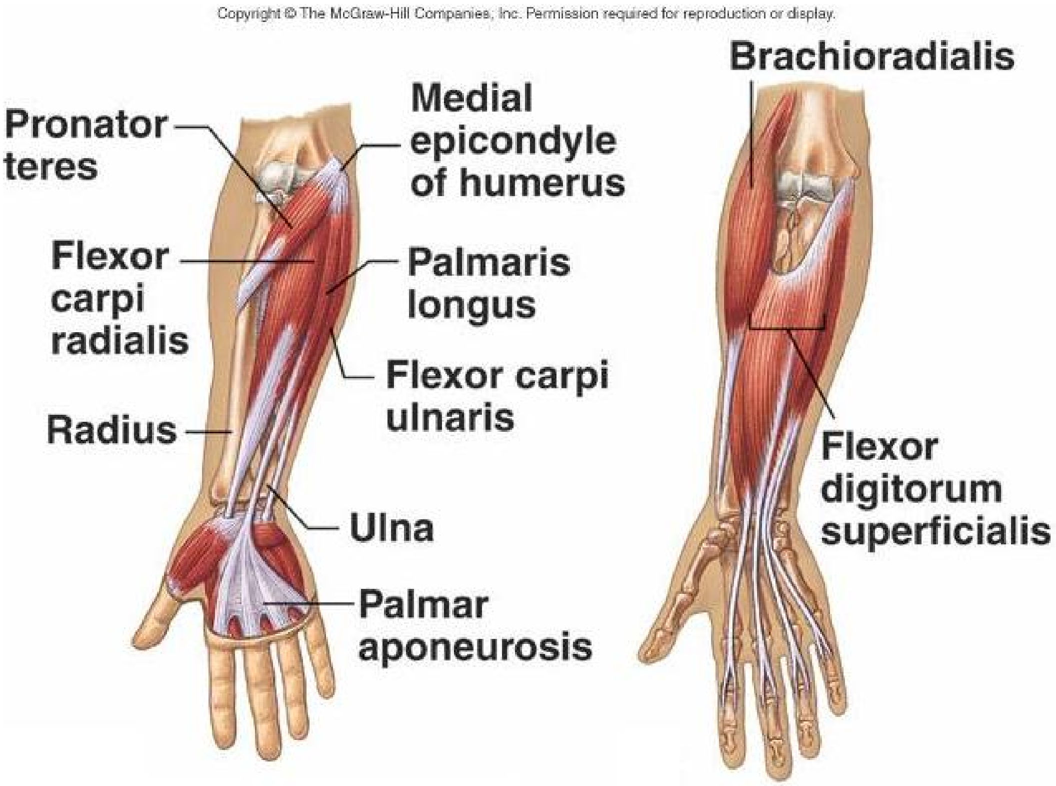

Figure 3. 4. Chosen Muscle Groups

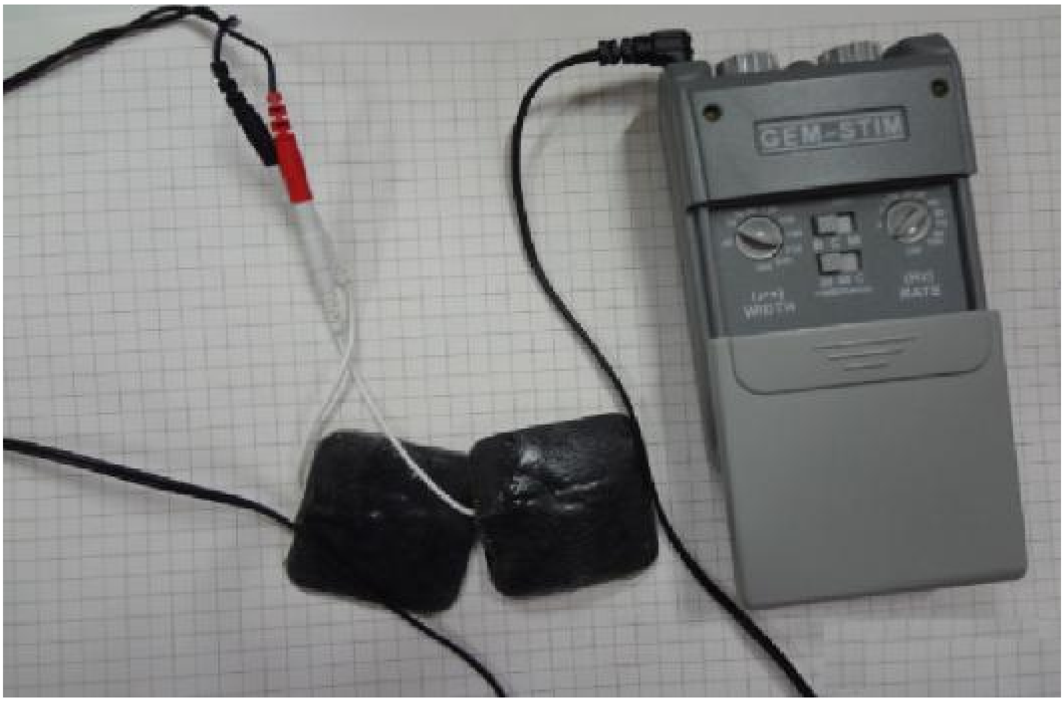

Figure 3.5. Muscle stimulator device

3.4. Used Surface Electrodes

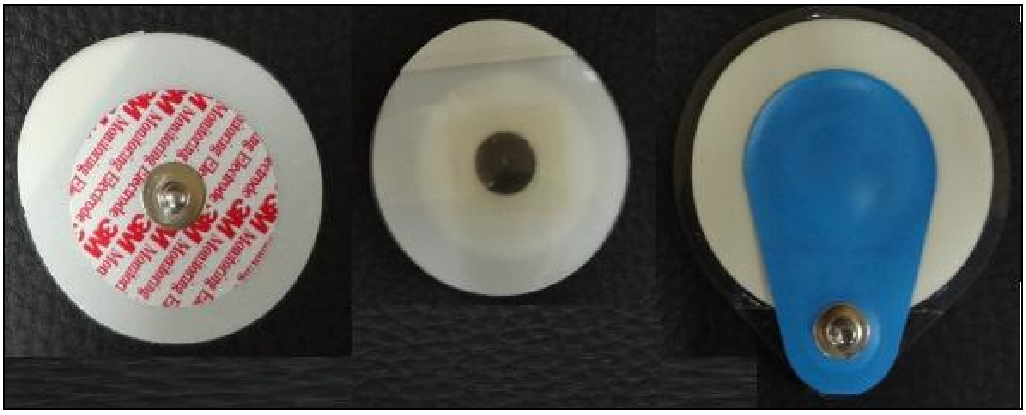

Figure 3.6. Used Surface electrodes

The EMG signals have been recorded in laboratory of sport and physiology of medicine faculty of the Cukurova university from five female and one male whose are 20,22,23,24,25,27 years old. The number of trails for each subject were different and they were 721,860,799,470,1150 and 421.

Figure 3.7. EMG recording device

3.5. EMG Signal Processing

A raw EMG signal offers us useless information. This information is useful if it can be quantified. Signal-processing methods processes the raw EMG signal to extract useful information from the EMG signal. The analysis methods are described below.Designed notch filter and how it eliminates a 50Hz are shown below.

3.6. Removal Of Power Line-Interference

Medical signals are subject to the power noise. Therefore it is required to suppress the power line signal added in the EMG. A notch filter does the removal the frequency of the power line (50Hz). The second-order discrete IIR notch filter transfer function is defined by:

$$H(z) = \frac{1-2\cos\left(\frac{2\pi f_{notch}}{f_s}\right)z^{-1}+z^{-2}}{1-2r\cos\left(\frac{2\pi f_{notch}}{f_s}\right)z^{-1}+r^2 z^{-2}} \tag{3.1}$$

Where r = 0.95, quality factor=5, bw=0.02, length of filter=101 and f_s=1000.

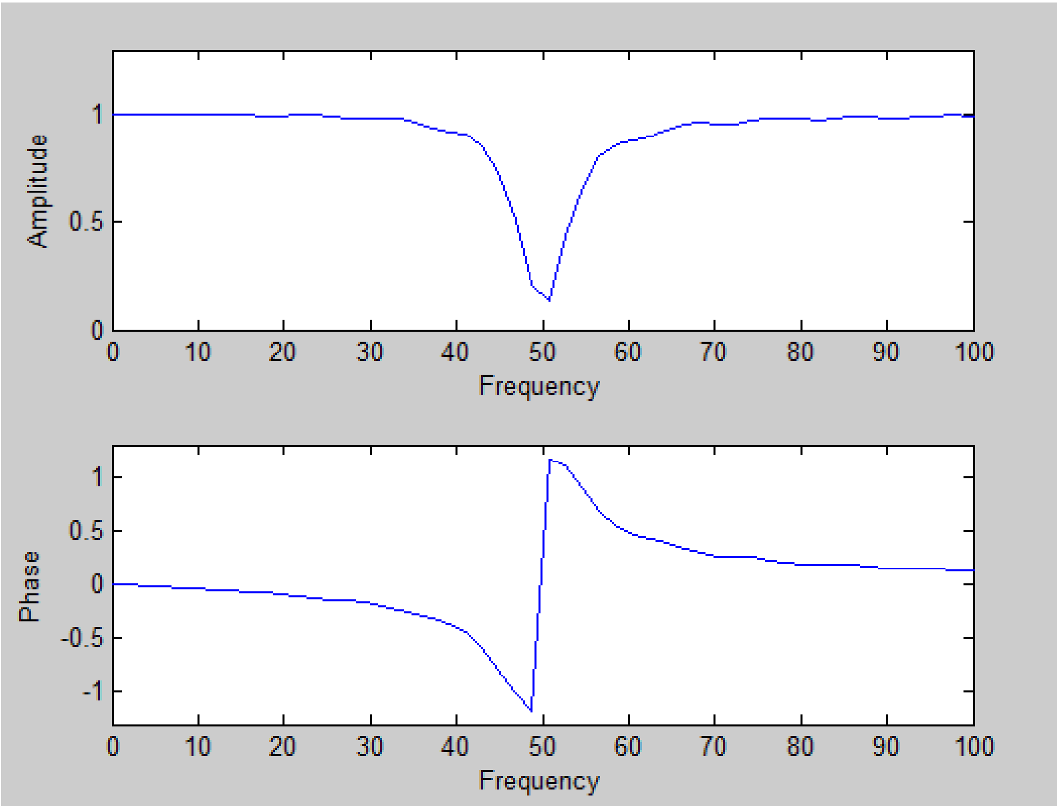

Figure 3. 8. Frequency and phase of notch filter

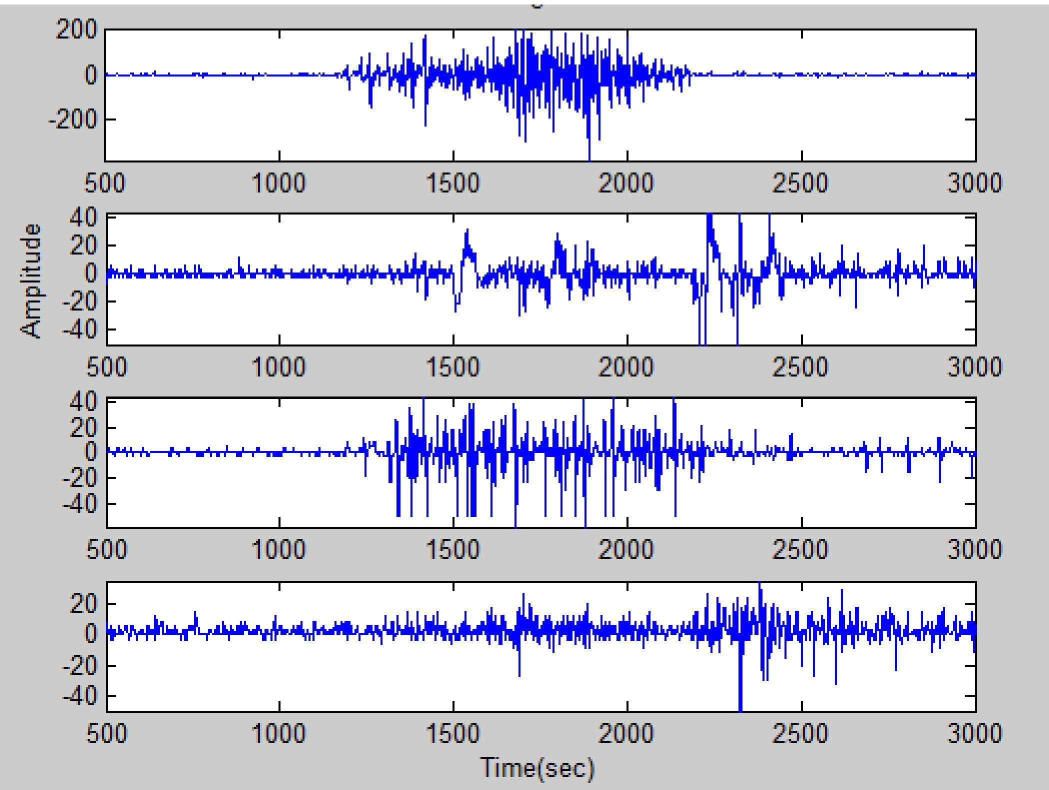

Figure 3. 9. Raw EMG signal

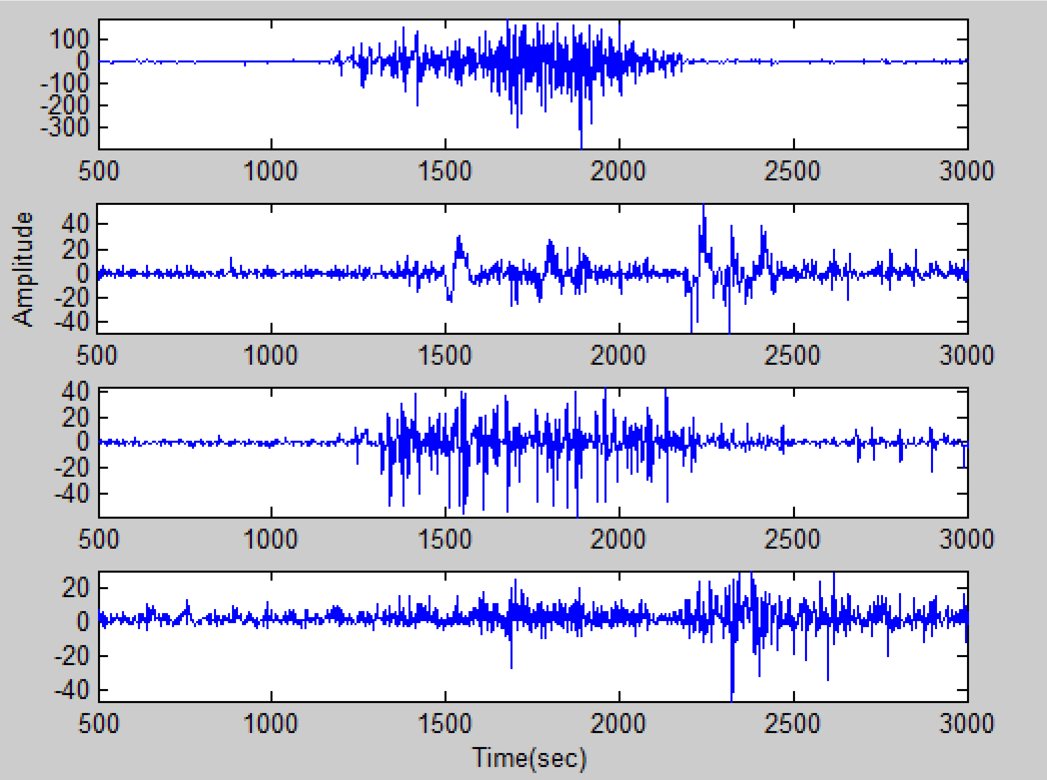

Figure 3. 10. Signal after notch filtering

3.7. Noise Removal By Digital Filtering

The base line wonder and high frequency noise are reduced by digital filtering. The finite-length (FIR) filters are linear phase (all the frequency components in an EMG are shifted by the same amount) and stable. These properties make the FIR filter appropriate for removing noise in EMG signals. A simple design method of an FIR filter is the Fourier series method. The coefficients of a low-pass filter with a cut-off frequency ω_0 rad/s and the length 2N+1 is:

$$h(n) = \frac{\sin(\omega_0 n)}{\pi n} . \cos\frac{\pi}{N} n, \qquad n = -N \ldots N \tag{3.2}$$

Where the length of the low-pass FIR filter is 101 and cut off frequency is 180.

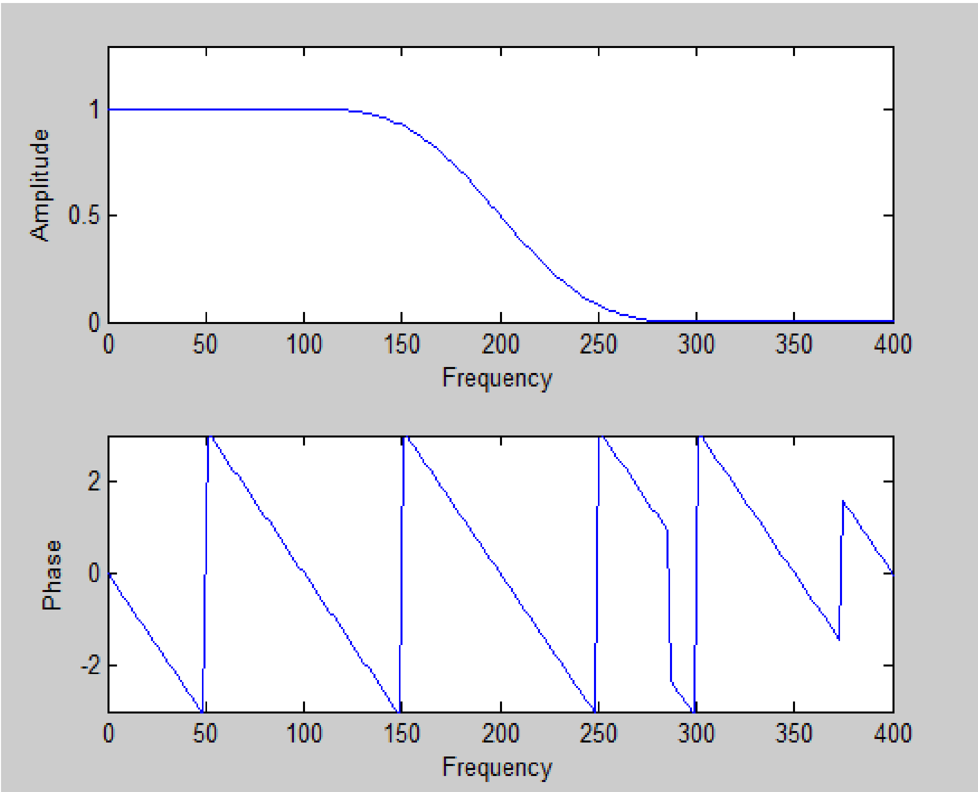

Figure 3. 11. Frequency and phase of FIR filter

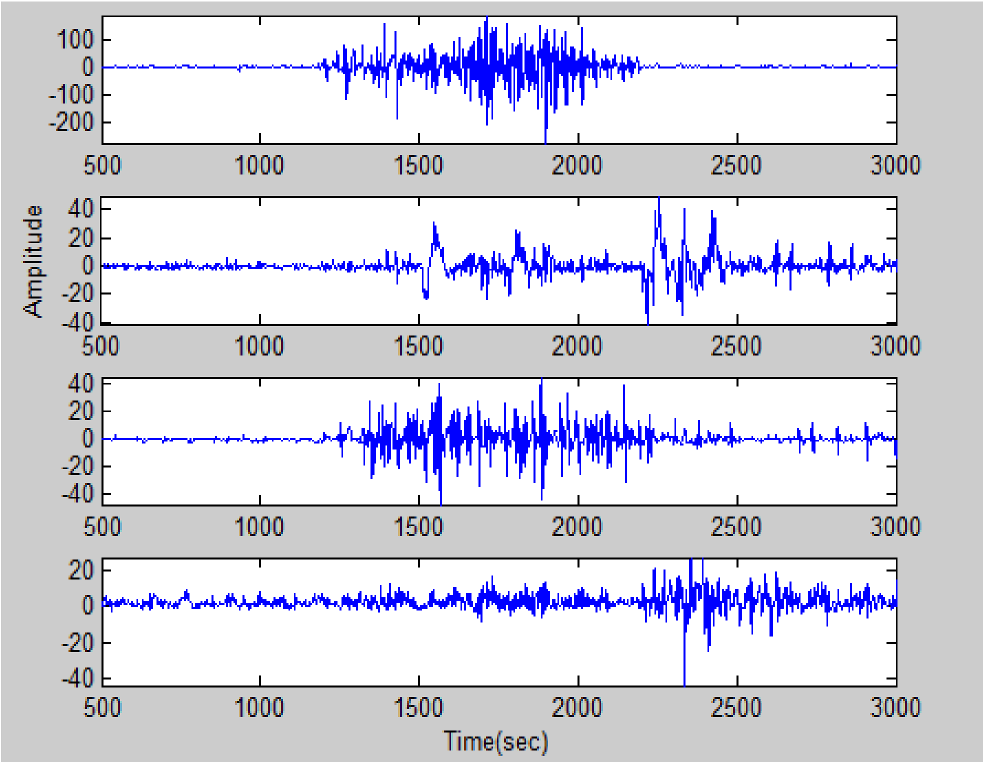

Figure 3. 12. Signal after low-pass FIR filtering

3.8. Signal Segmentation

We have four channels and five different hand movement. First for every hand movement biggest value of the four channels is chosen. The biggest value of a chosen channel is the reference point. The reference point indicates by t_i. All four channels follows reference point in the same segmentation.

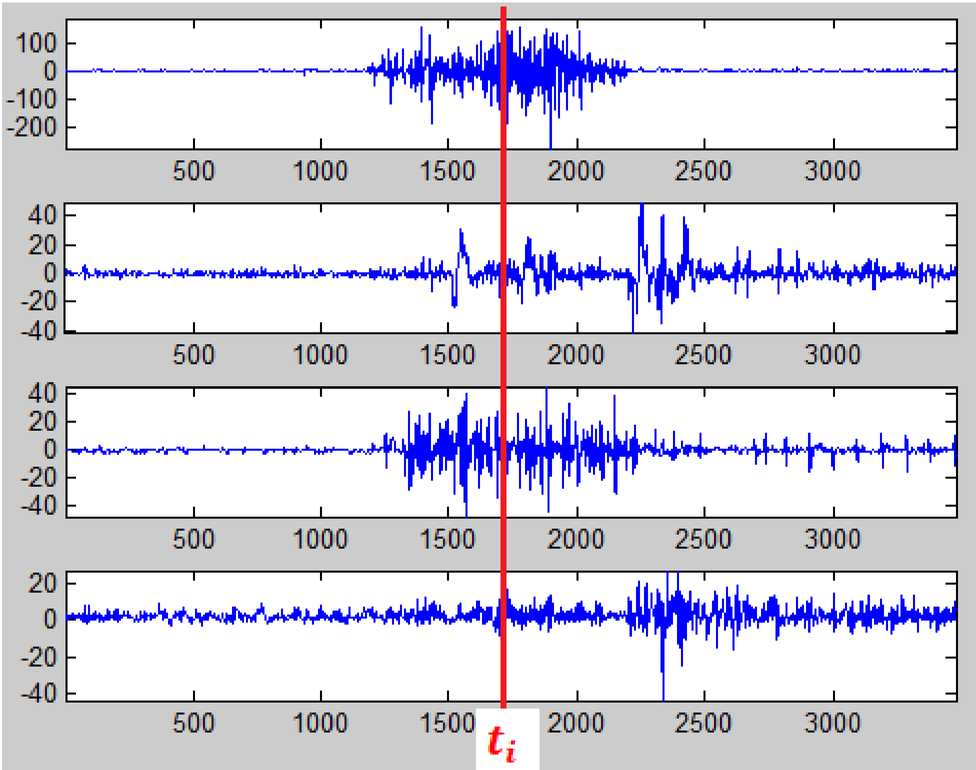

Figure 3. 13. Finding a reference point

In the next step sample is chosen around the reference point as defined below:

$$[\, t_i - \frac{L-1}{2} : t_i + \frac{L-1}{2} \,] \quad \text{for odd L}$$

$$[\, t_i - \frac{L}{2} : t_i + \frac{L}{2} \,] \quad \text{for even L}$$

Where $L = 2^R$ is the length of the segment that is chosen 512, 256 and 128.

Then every interval around t_i are segmented as follows:

a) $\boxed{\quad I \quad}$

In this interval each of every feature extraction is used.

b)

I	II

In part one and part two each of every feature extraction is used as some of them are shown below:

1) (Mean Power, Mean Power)
2) (Peak value, Peak value)
3) (Mean Frequency, Mean frequency)
4) (Frequency estimation, Frequency Estimation)
5) (Mean Power, Mean frequency)
6) (Peak Value, Frequency Estimation)

c)

I	II	III	IV

Every interval around t_i is divided into the four parts. For each parts features are calculated as some of them are shown below:

1) (Mean Power, Mean Frequency, Mean Power, Mean Frequency)
2) (Peak Value, Mean Frequency, Peak Value, Mean Frequency)

3.9. Feature Extraction

This phase involves extracting those features of the signal that display certain characteristic properties of EMG signal that are unique to the signal and are thus suitable for the classification purpose. Various techniques can be grouped in three main categories: time domain, frequency domain and time frequency domain (time-scale). Time domain features (TD) are frequently used for myoelectric classification because they are computationally simple (Zecca, Micera and Carrozza 2002). Various techniques like the neural network feature selector, mean absolute value, mean absolute value slope, Cepstrum coefficients, signal variance, waveform length, autoregressive (AR) model coefficients and Willison amplitude can be used for identifying the electrodes that provide better discriminatory information (Hudgins, Parker and Scott 1993) (Kuiken, et al. 2009) (Sensinger, Lock and Kuiken 2009) (M. Zardoshti-Kermani, et al. 1995) (Graupe, Salahi and Zhang 1985).

Frequency domain features present information about spectrum and are influenced by two factors: the firing rate of the motor units and the morphology of the action potential travelling along the muscle fibers (Karlsson, Jun and Akay 1999). The power spectral density (PSD) based on the Fourier transform is commonly used to perform a spectral analysis of the myoelectric signal. The mean and median frequency of the PSD can be estimated using either the classic periodogram (Merletti and Lo Conte, Surface EMG signal processing during isometric contractions 1997) or parametric methods such as regressive (AR) models (Paiss and Inbar 1987). Few studies have investigated the use of frequency domain features in pattern recognition schemes (Farry, Walker and Baraniuk 1996), (Sijiang and Vuskovic 2004) (Gallant, Morin and Peppard 1998) because the non-stationary nature of the myoelectric signal (De Luca and Carlo 1979) (Zecca, Micera and Carrozza 2002) is not captured by the Fourier transform.

Time-frequency representations (TFR) are special tools used to analyze non-stationary process that capture the time and frequency information present in the observed signal. In real-time signal classification applications, linear TFRs (i.e. The short time Fourier transform (STFT), the discrete wavelet transform (DWT) and the wavelet packet transform (WPT)) are preferable to quadratic TFRs (continuous wavelet transform (CWT)) because of their computational efficiency (Zecca, Micera and Carrozza 2002).

Below the feature extraction methods employed in this study are reported.

3.9.1. Mean – Power

It is average of the square EMG signal. It shows the strength of the EMG signal.

$$\boldsymbol{P} = \frac{1}{N}\sum_{n=0}^{N-1} X^2(n) \tag{3.3}$$

Where N is the length of the signal.

3.9.2. Peak – Value

To compute the envelope Hilbert transform is employed (S. Haykin 1994):

$$\textbf{Peak value} = \max\left(\sqrt{X^2(n) + \hat{X}^2(n)}\right) \tag{3.4}$$

Where $\hat{X}^2(n)$is Hilbert transform of $X(n)$, and $X_+(n)$is Pre-envelope of X (n) and $\sqrt{X^2(n) + \hat{X}^2(n)}$ is the envelope of X(n).

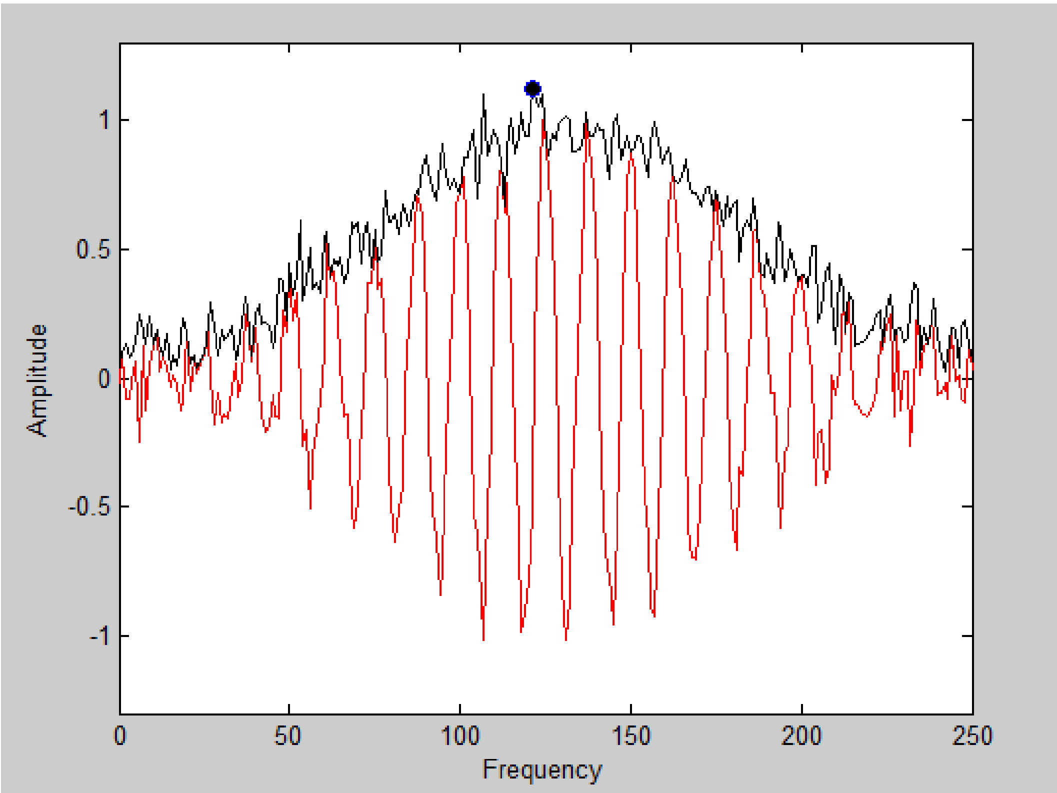

Figure 3. 14. Peak value of EMG signal by envelope

3.9.3. Mean – Frequency

The mean frequency is also computed. It is related to the power generated by the muscle and the weariness of the muscle.

$$X(k) = \sum_{n=0}^{N-1} x(n)\, \omega(n)\, e^{-i\frac{2\pi}{N}k\,n} \tag{3.5}$$

$$k_a = \frac{\sum_{k=0}^{N-1} |X(k)|^2 . k}{\sum_{k=0}^{N-1} |X(k)|^2} \tag{3.6}$$

Where k_a is frequency index and $\omega(n)$ is Hamming window.

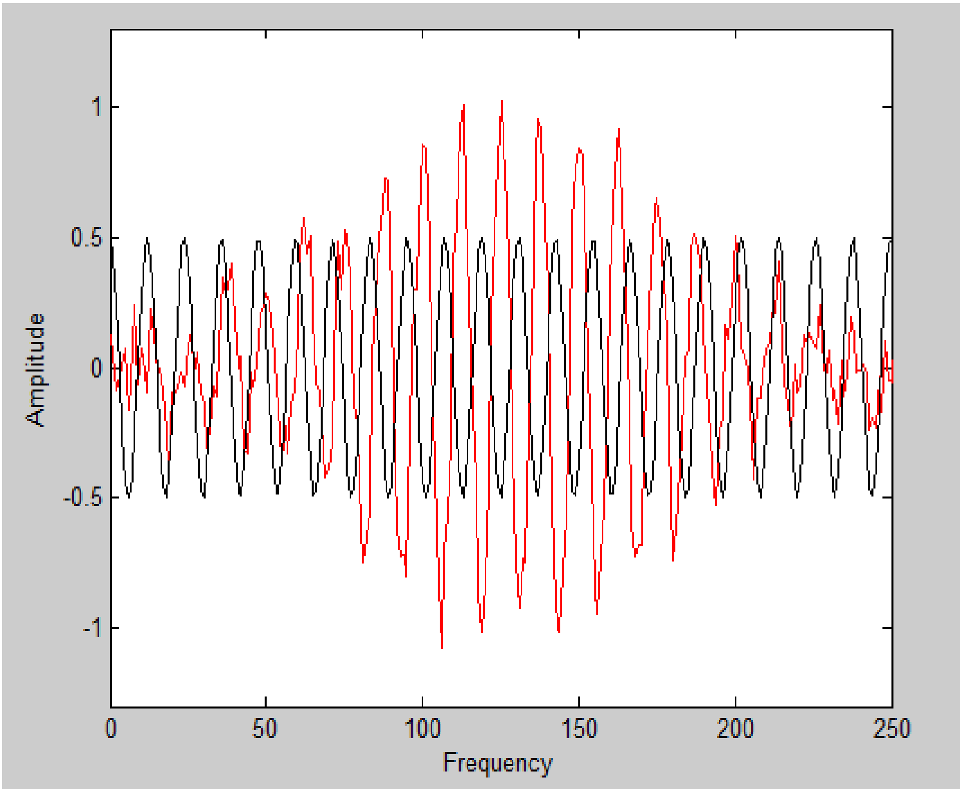

Figure 3. 15.A burst and its mean frequency as an oscillation

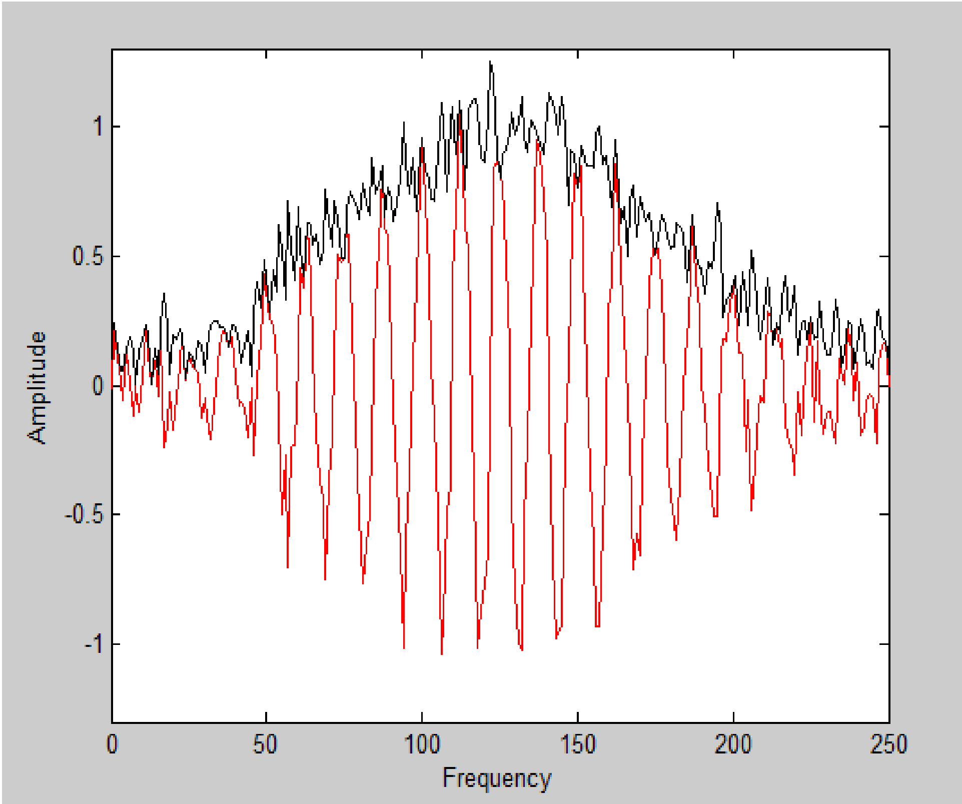

Figure 3. 16. Envelope of Mean frequency of EMG signal

3.9.4. Frequency Estimation By MUSIC Method

Frequency estimation is the process of estimating the complex frequency components of a signal in the presence of noise, given assumptions about the number of the components. There are methods involve identifying the noise subspace to extract these components. These methods are Pisarenko' s Method, Multiple signal classification (MUSIC), the eigenvector solution, and the minimum norm solution.

The used method of frequency estimation is Music method. In 1979, the MUSIC algorithm as a frequency estimation technique, was presented by Schmid. The dominant frequency can alternatively be obtained by the music frequency estimation method. In this method the covariance of the matrix of x (n) needs to be computed. Next eigenvalues and eigenvectors of the covariance matrix are extracted. To see how the MUSIC algorithm works, assume that x (n) is a random process consisting of p complex exponentials in the presence of Gaussian white noise and let R_x be the M * M autocorrelation matrix of x(n) with M > p+1. If the eigenvalues are sorted in decreasing order, $\lambda 1 \geq \lambda 2 \geq \cdots \geq \lambda_M$, and if v1, v2,.., v_M are the corresponding eigenvectors, then we may divide theses eigenvectors into two groups: the p signal eigenvectors corresponding to the p largest eigenvalues, and the M – p noise eigenvectors that, ideally, have eigenvalues equal to σ_ω^2. Note that for M = p + 1, MUSIC is identical to Pisarenko harmonic decomposition. The general idea is to use averaging to improve the performance of the Pisarenko estimator. The frequency estimation function for MUSIC is (HAYES 1996):

$$\hat{P}_{MU}\left(e^{j\omega}\right) = \frac{1}{\sum_{i=p+1}^{M} \left| e^H v_i \right|^2} \tag{3.7}$$

Where v_i are the noise eigenvectors and

$$e = \left[1 \quad e^{j\omega} e^{j2\omega} \ \ldots \quad e^{j(M-1)\omega}\right]^T \tag{3.8}$$

The locations of the p largest peaks of the estimation function give the frequency estimates for the p signal components (HAYES 1996).

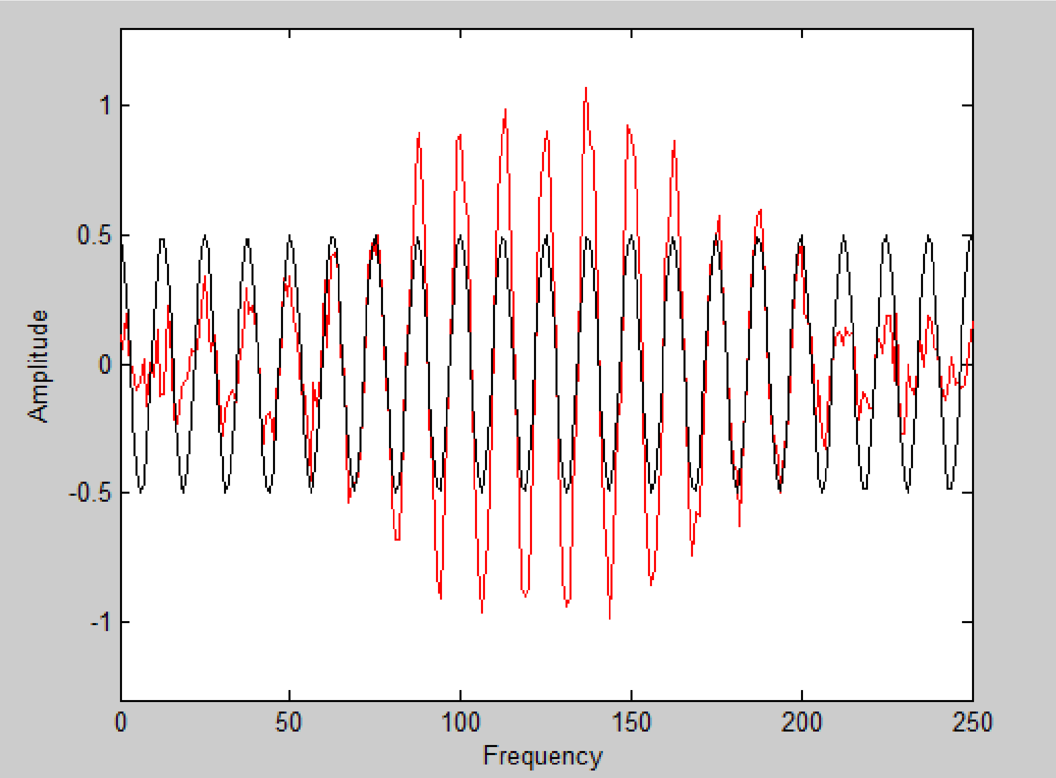

Figure 3. 17. A burst and its frequency estimation as an oscillation

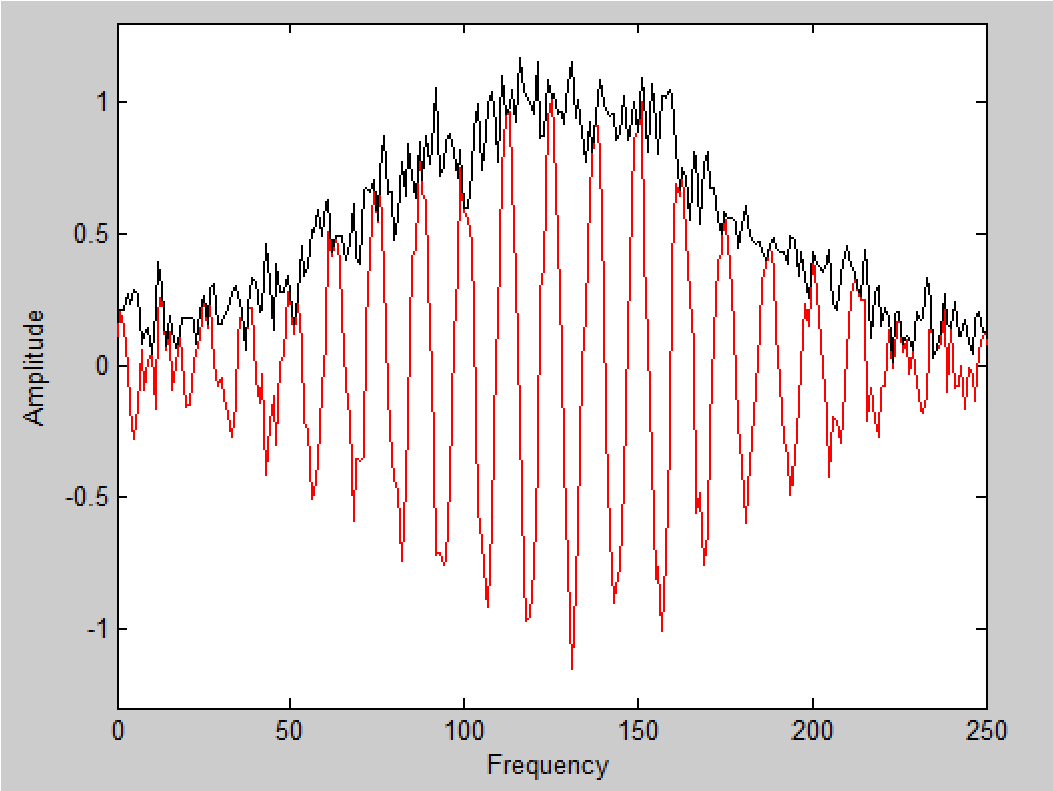

Figure 3. 18. Envelope of frequency estimation of EMG signal

3.10. The Classifiers

Different types of algorithms have been employed to classify EMG signals, such as, linear discriminant analysis (LDA), radial basis function neural networks, fuzzy networks, Gaussian mixture models and hidden Markov models (Oskoei and Huosheng 2008). Nowadays, some researchers have begun to employ support vector machines to EMG analysis (Oskoei and Huosheng 2008) (Yoshikawa, Mikawa and Tanaka 2006) (Yi-Hung Liu, Han-Pang Huang and Chang-Hsin Weng 2007) (Rekhi, et al. 2009).

3.10.1. Bayes Classifier

Classification is a process where the unknown labels of test data are predicted. Normally, for classification studies, we have three types of dataset: training, validation and testing. The class labels of the training and validation dataset are known, while for testing data, the class labels are known. The training process is where a classification model/decision rule is formed using the training dataset while the validation dataset is used to decide the best parameters for the model. The validation dataset is also used to obtain a performance measure on the goodness of the model by classifying i.e. predicting the validation dataset class labels and comparing with the actual labels. If the performance measure is satisfactory, the obtained classification model could then be used to predict the unknown classes of the test dataset and this is known as testing process (Palaniappan 2010).

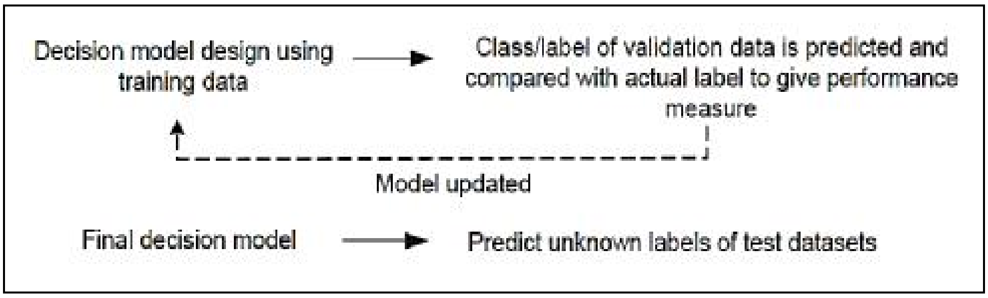

Figure 3.19. Classification procedure (training and testing) (Palaniappan 2010)

Bayes' theorem is a theorem of probability theory originally stated by the Reverend Tomas Bayes. This theorem is a simple mathematical formula used for calculating conditional probabilities. It allows us to calculate the probability of an earlier event, given the result of a later event. The theorem provides a way to revise existing predictions or theories given new evidence. Bayes' theorem shows the relation between a conditional probability and its reverse form. The minimum error rate discriminant function for multiple category is (Alpaydin 2004):

$$g_k(x) = P(w_k|x) \tag{3.9}$$

$$g_k(\vec{x}) = \ln(p(x|w_k)P(w_k)) \tag{3.10}$$

In case $\Sigma_j = \Sigma$ (covariance of all classes is identical)

$$g_j(\vec{x}) = \vec{w}_j^t \vec{x} + w_{j0} \tag{3.11}$$

Where:

$$\vec{w}_j = \Sigma^{-1}\vec{\mu}_j \tag{3.12}$$

$$w_{j0} = -\frac{1}{2}\vec{\mu}_j^t\Sigma^{-1}\vec{\mu}_j + \text{Ln } P(w_j) \tag{3.13}$$

3.10.2. LDA (Linear Discriminant Analysis) Classification

There are many techniques for classification of data. Linear Discriminant Analysis (LDA) and Principal Component Analysis (PCA) are two commonly used techniques for data classification. LDA method minimizes space between data of every class that called within-class scatter and maximizes space between every aggregation of classes that called between-class scatter. There are a lot of different between LDA and PC. The first difference between LDA and PCA is PCA does more of feature classification and LDA does data classification. In PCA, the shape and location of the original data set changes when transformed into a different space whereas LDA doesn' t change the location but only tries to provide more class separability and draw a decision region between the given classes.This method also helps to better understand the distribution of the feature data.

Within-class scatter and between-class scatter can be calculated by:

$$S_W = \frac{1}{N}\sum_{i=1}^{c}\sum_{x \in C_i}(x - m_i)(x - m_i)^T \tag{3.14}$$

$$S_b = \frac{1}{N}\sum_{i=1}^{c} N_i\,(m_i - m)(m_i - m)^T \tag{3.15}$$

Suppose we have N data and c class. In these equations m is the average of the whole of the data and m_i is the average of within classes of i. N_i represents number of data within class i. To minimize within-class scatter and maximize between-class scatter in the same time equation (3.30) that called Fisher index have to be maximized (Harandi 2009)(Balakrishnama and Ganapathiraju n.d.).

$$W_{opt} = \arg_w \max \left(\frac{|w^T s_b w|}{|w^T s_b w|} \right) \quad (3.16)$$

If $W_{opt}.x + b > 0$, class1

If $W_{opt}.x + b < 0$, class2

3.10.3. Support Vector Machines For Classification

The original SVM algorithm was invented by Vladimir N. Vapnik and the current standard incarnation (soft margin) was proposed by Vapnik and CorinnaCortes in 1995 (Cortes and Vapnik 1995).

SVMs can be described as binary classifiers, which determine whether a sample belongs to one class or another (Haykin 1999). The classifier should be able to learn the different muscle contraction patterns selected to stimulate the prosthetic hand.

A support vector machine constructs a hyperplaneor a set of hyperplanes in a high or infinite-dimensional space, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalizationerror of the classifier. In this case, the optimal hyperplane can be described by the following equation (Burges 1998):

$$\mathbf{y(x) = w^T \varphi(x) + b} \quad (3.17)$$

Where w and b are the parameters of the hyperplane and $\varphi(x)$ represents the feature space transformation.

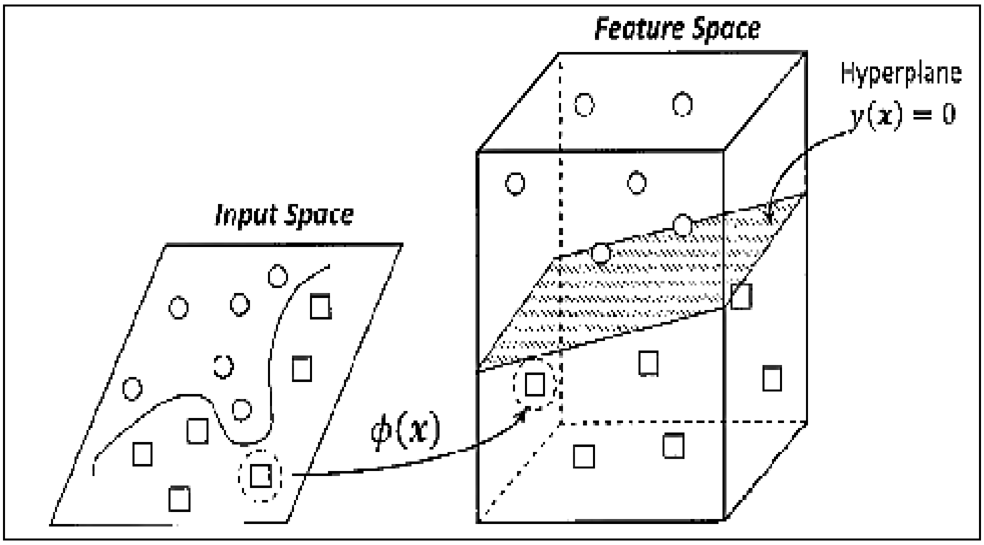

Figure 3.10. After transforming data into a new feature space, SVM finds a linear decision surface that separates the input data (Fontana 2010).

Data can be separated with a simple line too (Haykin 1999). In this case, the optimal hyperplane can be described by:

$$\mathbf{w}^{\mathbf{T}}\mathbf{x} - \mathbf{b} = \mathbf{0} \tag{3.18}$$

Where w represents a weight vector and x represents an input vector. Figure 3.8 shows an example of an optimal hyperplane with linearly separable data in two dimensions. Once the optimal hyperplane is determined a particular set of input vectors are used to define this hyperplane, which are called support vectors. As seen in Figure 3.10 these vectors are typically those input vectors that lie closest to the optimal hyperplane. For any new samples xi, classification is then performed based on the following conditions (Haykin 1999)

$$\text{if} \quad \mathbf{w}^{\mathbf{T}}\mathbf{x}_{\mathbf{i}} - \mathbf{b} \geq \mathbf{0}\mathbf{y}_{\mathbf{i}} = +\mathbf{1} \tag{3.19}$$

$$\text{if} \quad \mathbf{w}^{\mathbf{T}}\mathbf{x}_{\mathbf{i}} - \mathbf{b} < \mathbf{0}\mathbf{y}_{\mathbf{i}} = -\mathbf{1} \tag{3.20}$$

Where $\mathbf{x}_{\mathbf{i}}$ is the $\mathbf{i}^{\mathbf{th}}$ sample and $\mathbf{y}_{\mathbf{i}}$is the $\mathbf{i}^{\mathbf{th}}$ output(Haykin 1999).

By using geometry, we find the distance between these two hyperplanes is $\frac{2}{||w||}$, so we want to minimize ||w||. We also have to prevent data points from falling into the margin, we add the following constraint:

$w^T x_i - b \geq 1$ for x_i of the first class

$w^T x_i - b \leq -1$ for x_i of the second class

This can be rewritten as:

$y_i(w^T x_i - b) \geq 1$ for all $1 \leq i \leq n$.

We can use this formula and minimize w and b to get the optimization problem.

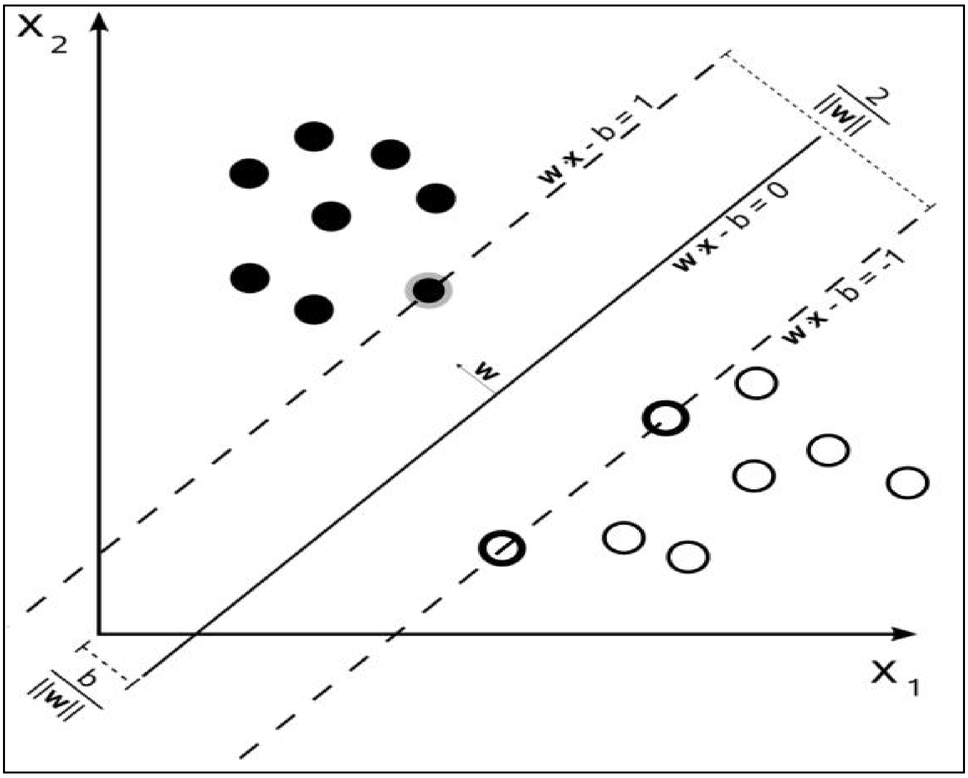

Figure 3.201. Maximum-margin hyperplane and margins for an SVM trained with samples from two classes. Samples on the margin are called the support vectors (Haykin 1999).

SVM is never designed as multiclass classifier. So Matlab like its basic principle supports only two classes. In this study we have five hand movements and classes. For solving this problem we made an array by five columns for every class and compared classes one by one as two classes and the largest value of the classes determined.

4. RESULTS

In this part the classification results are reported. For window lengths; 512, 256, 128 and feature types; Mean power, Mean frequency, Peak value, Frequency estimation the experiment is realized. Inter-subject and intra-subject movement prediction and estimation of right hand movements from left hand movements (and vice-versa).

We divided every subject into two parts. One part for training and another part for testing and inverse (2-fold cross validation).In inter-subject we chose random data from per index for 20 times. In intra-subject the average of the every subject is obtained.

Table 4.1. Inter-subject classification performances of subject1 obtained by 2-fold cross validation with Bayes classifier

Window size / Features	512	256	128
P	%88.57	%86.94	%84.29
$\tilde{X}^2$	%81.58	%80.02	%77.22
$\hat{f}$	%81.57	%75.93	%66.89
(P_1,P_2)	%82.20	%80.29	%79.44
$(\tilde{X}_1^2,\tilde{X}_2^2)$	%77.29	%74.58	%70.21
$(\hat{f}_1,\hat{f}_2)$	%76.21	%66.68	%54.09

Table 4.2. Average classification performances of subject1, subject2 and subject3 obtained by 2-fold cross validation for the window size 512

Features	Inter-sub		Intra-sub	
	Bayes	SVM	Bayes	SVM
$\tilde{X}^2$	%81.4	%70	%58.9	%54.7
$\hat{f}$	%85.4	%74	%58.8	%53
$(\tilde{X}_1^2,\tilde{X}_2^2)$	%78.2	%71.7	%58.6	%57.2
$(\hat{f}_1,\hat{f}_2)$	%81.4	%76	%59.1	%52

Because of the covariance problem, segmentation type of (Mean Power, Mean Frequency, Mean Power, Mean Frequency) against with an error. In the next parts this problem is solved by usingthe SVM classifier.

Classification performance is validated by using four-fold cross validation method. In this part we divide per subject into a, b, c, d parts as called 4-fold validation method. Then we chose 3/4 for training and 1/4 for testing as is shown:

1. a, b, c for training and d for testing (A).
2. a, c, d for training and b for testing (B).
3. a, b, d for training and c for testing (C).
4. b, c, d for training and a for testing (D).

Table 4.3.Inter-subject classification performances of subject1, subject2 and subject3 obtained by 4-fold cross validationfor the window size 512

Features		$\bar{X}^2$	$\hat{f}$	$(\bar{X}_1^2, \bar{X}_2^2)$	$(\hat{f}_1, \hat{f}_2)$	$(\bar{X}_1^2, \hat{f}_1, \bar{X}_2^2, \hat{f}_2)$
A	Bayes	%82	%89	%80	%86	%90
	LDA	%80	%88	%80	%86	%89
B	Bayes	%85	%93	%88	%95	%98
	LDA	%84	%92	%88	%94	%97
C	Bayes	%81	%88	%80	%86	%89
	LDA	%80	%87	%80	%86	%88
D	Bayes	%81	%88	%79	%87	%89
	LDA	%80	%87	%78	%87	%88
Average	Bayes	%82.25	%89.5	%81.75	%86	%91.5
	LDA	%81	%88.5	%81.5	%88.25	%90.5

LDA and Bayes classifiers have the same results in intra-subjects but results of inter-subjects in Bayes classifier are better than LDA classifier.

Same as Table 4.3 are done for 256 and 128 window lengths as is shown in Tables (4.4) and (4.5).

Table 4.4. Inter-subject classification performances of subject1, subject2 and subject3 obtained by 4-fold cross validationwith Bayes classifier for the window size 256

Features	A	B	C	D	Average
$\bar{X}^2$	%79	%84	%78	%80	%80.25
$\hat{f}$	%82	%89	%81	%82	%83.5
$(\bar{X}_1^2, \bar{X}_2^2)$	%78	%87	%78	%77	%80
$(\hat{f}_1, \hat{f}_2)$	%79	%92	%78	%80	%82.25
$(\bar{X}_1^2, \hat{f}_1, \bar{X}_2^2, \hat{f}_2)$	%87	%98	%87	%85	%89.25

Table 4.5. Inter-subject classification performances of subject1, subject2 and subject3 obtained by 4-fold cross validationwith Bayes classifier for the window size 128

Features	A	B	C	D	Average
$\bar{X}^2$	%77	%81	%76	%75	%77.25
$\hat{f}$	%74	%84	%75	%74	%76.75
$(\bar{X}_1^2, \bar{X}_2^2)$	%73	%85	%75	%74	%76.75
$(\hat{f}_1, \hat{f}_2)$	%70	%88	%70	%70	%74.5
$(\bar{X}_1^2, \hat{f}_1, \bar{X}_2^2, \hat{f}_2)$	%81	%97	%82	%80	%85

The four-fold validation method is investigated for different features with Bayes classifier as shown in Table (4.6).

Table 4.6. Inter-subject classification performances of subject1 obtained by 4-fold cross validationwith Bayes classifier for the window size 512

Features	A	B	C	D	Average
p	%92.92	%94.33	%91.21	%90.32	%92.19
$\tilde{X}^2$	%81.69	%87.32	%82.08	%81.22	%83.07
$\hat{f}$	%85.88	%93.13	%85.9	%85.3	%87.55
(P_1,P_2)	%85.05	%97.1	%87.09	%86.72	%88.99
$(\tilde{X}_1^2,\tilde{X}_2^2)$	%78.8	%90.88	%80.75	%78.52	%82.23
$(\hat{f}_1,\hat{f}_2)$	%84.51	%96.23	%83.91	%84.27	%87.23
$(P_1,\hat{f}_1, P_2,\hat{f}_2)$	%88.09	%99.61	%86.75	%85.25	%89.92
$(\tilde{X}_1^2,\hat{f}_1,\tilde{X}_2^2,\hat{f}_2)$	%85.41	%99.3	%82.65	%82.89	%87.56

We also used frequency estimation for feature extraction of the EMG signal. All the studies have been done for 512,256 and 128 window lengths as shown in Tables (4.7).

Table 4.7. Inter-subject classification performances of subject1, subject2 and subject3 obtained by 4-fold cross validationwith Bayes classifier for frequency estimation features

Features		512	256	128
A	fs	%82.2	%75	%66.8
	(fs_1,fs_2)	%80.8	%71.2	%61.2
B	fs	%89.7	%84.1	%79.1
	(fs_1,fs_2)	%92.7	%88.3	%83
C	fs	%82.8	%74.3	%67.2
	(fs_1,fs_2)	%80.6	%70.2	%60.1
D	fs	%82.2	%74.6	%68.5
	(fs_1,fs_2)	%80.9	%71.2	%60.4
Average	fs	%84.22	%77	%70.4
	(fs_1,fs_2)	%83.75	%75.22	%66.17

The two-fold validation method is investigated for different features with SVM classifier as shown in Table (4.8).

Table 4.8. 2-fold validation method and intra-sub for subject1, subject2 and subject3

Features	512 SVM		256 SVM		128 SVM	
	Inter Subject	Intra Subject	Inter Subject	Intra Subject	Inter Subject	Intra Subject
P	%73	%58.9	%72	%58.4	%70	%56.1
$\hat{X}^2$	%70	%54.7	%68.1	%54.2	%66.6	%52.4
fs	%66	%44.3	%58	%41.7	%51	%39.5
$\hat{f}$	%74	%53	%67	%48	%59	%45
(P_1,P_2)	%78	%60.9	%76	%60.2	%74	%57.8
$(\hat{X}_1^2,\hat{X}_2^2)$	%71.7	%57.2	%69.3	%56.2	%67.8	%53
(fs_1,fs_2)	%65	%46.9	%54	%40.8	%47	%37.7
$(\hat{f}_1,\hat{f}_2)$	%76	%52	%65	%47	%56	%45
(P_1,fs_1,P_2,fs_2)	%89	%71.8	%86	%68.7	%81	%67
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%92	%70.6	%88	%68.9	%84	%66.3

The same thing in inter-subjectone by one is done for subject1, subject2 and subject3as shown in the Tables (4.9), (4.10), (4.11).

Table 4.9. 2-fold validation method for subject1 by SVM classifier

Features	512	256	128
	Sub1	Sub1	Sub1
P	%82.6	%83.84	%78.43
$\hat{X}^2$	%76.04	%75.1	%74.12
$\hat{f}$	%73.7	%66.99	%56.88
(P_1,P_2)	%87.49	%86.55	%83.69
$(\hat{X}_1^2,\hat{X}_2^2)$	%76.93	%75.07	%74.65
$(\hat{f}_1,\hat{f}_2)$	%74.95	%5.94	%49.26
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%92.16	%91.46	%86.5

Table 4.10. 2-fold validation method for subject2 by SVM classifier

Features	512 Sub2	256 Sub2	128 Sub2
P	%60.96	%57.85	%57.92
$\bar{X}^2$	%64.43	%60.17	%55.25
$\hat{f}$	%74.05	%68.06	%61.08
(P_1,P_2)	%65.1	%62.65	%59.58
$(\bar{X}_1^2,\bar{X}_2^2)$	%65.81	%62.14	%57
$(\hat{f}_1,\hat{f}_2)$	%75.93	%62.91	%58.01
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%86.17	%77.67	%76.07

Table 4.11. 2-fold validation method for subject3 by SVM classifier

Features	512 Sub3	256 Sub3	128 Sub3
P	%73.42	%72.89	%75.26
$\bar{X}^2$	%68.14	%67.85	%67.05
$\hat{f}$	%77.52	%69.7	%60.5
(P_1,P_2)	%78.21	%76.91	%75.45
$(\bar{X}_1^2,\bar{X}_2^2)$	%71.24	%69.54	%68.87
$(\hat{f}_1,\hat{f}_2)$	%76.4	%69.68	%62.67
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%93.76	%91.9	%88.15

In this section subject5is used. There are two sets of data from the left hand and four sets of data from the right hand of subject5. Left hand data are used for training, and the right hand of data is used for testing and inverse (4.12). The same thing is done for subject4 and subject6. There are fivesets of data from the left hand and four sets of data from the right hand of subject4 as is shown in Table (4.13).There are also threesets of data from the left hand and three sets of data from the right hand of subject4 as is shown in Table (4.14).

Table 4.12. Two sets of data from the left hand for training and four sets of data from the right hand for testing and reverse

Features	512 Sub5	256 Sub5	128 Sub5
	SVM	SVM	SVM
p	%63.1	%61	%57.6
$\hat{f}$	%53.8	%48.1	%37.9
(P_1,P_2)	%61.2	%59.1	%60.4
$(\hat{f}_1,\hat{f}_2)$	%53	%48.8	%39.8
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%71.6	%63.2	%58.6

Table 4.13. Five sets of data from the left hand for training and four sets of data from the right hand for testing and reverse

Features	512 Sub4	256 Sub4	128 Sub4
	SVM	SVM	SVM
p	%39	%47.1	%43.1
$\hat{f}$	%35.2	%32.8	%29.1
(P_1,P_2)	%41.3	%43.2	%42.3
$(\hat{f}_1,\hat{f}_2)$	%46.1	%34.5	%26.8
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%67.3	%65.2	%59.5

Table 4.14. Three sets of data from the left hand for training and three sets of data from the right hand for testing and reverse

Features	512 Sub6	256 Sub6	128 Sub6
	SVM	SVM	SVM
p	%55.6	%59.7	%58.1
$\hat{f}$	%58.4	%52.5	%47.9
(P_1,P_2)	%61.5	%58	%59.8
$(\hat{f}_1,\hat{f}_2)$	%60.3	%54	%50
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%76.8	%72.1	%69.4

In this part, first set of data from left hand is trained for every set of data from the right hand as is shown in Table (4.15). The same thing is done for the secondset of data fromthe left hand as is shown in Table (4.16).

Table 4.15. The first set of data from left hand is trained for every set of data from right hand

Features	512 Sub5	256 Sub5	128 Sub5
	SVM	SVM	SVM
p	%58.7	%53	%53
$\hat{f}$	%53.7	%50.2	%36.7
(P_1,P_2)	%57.5	%52.2	%54
$(\hat{f}_1,\hat{f}_2)$	%63	%50.5	%41.5
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%60.5	%56.7	%54

Table 4.16. The secondset of data from left hand is trained for every set of data from right hand

Features	512 Sub5	256 Sub5	128 Sub5
	SVM	SVM	SVM
p	%73.2	%72	%68.5
$\hat{f}$	%63.2	%55.2	%39
(P_1,P_2)	%72.5	%73.7	%75.7
$(\hat{f}_1,\hat{f}_2)$	%59.7	%54.7	%43.5
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%82.7	%66.7	%66.5

In this section, two sets of data from the left hand ofsubject5 one by one are trained for every three sets of data from the left hand of subject6 for testing and inverse as is shown in Table (4.17). The same things are done for, four sets of data from the right hand of subject5 for trainingand three sets of data from the right hand of subject6 for testing and inverseas is shown in Table (4.18).

Table 4.17. Intra left hand subjects

Features	512 Intra-sub	256 Intra-sub	128 Intra-sub
	SVM	SVM	SVM
p	%31.4	%30.5	%31.4
$\hat{f}$	%23.7	%22.7	%22.9
(P_1,P_2)	%29.8	%32.5	%30.7
$(\hat{f}_1,\hat{f}_2)$	%23.7	%23	%23.3
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%34.2	%36.2	%33.5

Table 4.18. Intra right hand subjects

Features	512 Intra-sub	256 Intra-sub	128 Intra-sub
	SVM	SVM	SVM
p	%35.6	%34.1	%33.7
$\hat{f}$	%35.4	%35.8	%32.9
(P_1,P_2)	%36.9	%36.3	%36.8
$(\hat{f}_1,\hat{f}_2)$	%32	%32	%33.3
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%35.5	%38.4	%37

In this section the first set of data from the right ofsubject5 is used for training and, sets of data from theleft hand of subject5 are used for testing as is shown in Table (4.19). This method is also done for second, third, and fourth right hand subjects for training as shown respectively in Tables(4.20), (4.21), (4.22).

Table 4.19. First set of data from the right hand for training and sets of the data from the left hand for testing

Features	512 Sub5	256 Sub5	128 Sub5
	SVM	SVM	SVM
P	%48.9	%43.5	%42.9
$\hat{f}$	%54.1	%48.6	%37
(P_1,P_2)	%42	%40.9	%45.7
$(\hat{f}_1,\hat{f}_2)$	%53.5	%45.7	%44.8
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%60.4	%57.2	%43.4

Table 4.20. Second set of data from the right hand for training and sets of the data from the left hand for testing

Features	512 Sub5	256 Sub5	128 Sub5
	SVM	SVM	SVM
P	%69.8	%72.7	%61.1
$\hat{f}$	%47.6	%34.6	%33.6
(P_1,P_2)	%69.8	%71.8	%67
$(\hat{f}_1,\hat{f}_2)$	%37	%36.2	%33.3
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%73.3	%59.3	%59.5

Table 4.21. Third set of data from the right hand for training and sets of the data from the left hand for testing

Features	512 Sub5	256 Sub5	128 Sub5
	SVM	SVM	SVM
P	%57.3	%61	%60
$\hat{f}$	%46.5	%39.2	%.33
(P_1,P_2)	%56	%52.3	%53.1
$(\hat{f}_1,\hat{f}_2)$	%42.7	%35	%23.8
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%81	%62.9	%56.2

Table 4.22. Fourth set of data from the right hand for training and sets of the data from the left hand for testing

Features	512 Sub5	256 Sub5	128 Sub5
	SVM	SVM	SVM
P	%64.9	%60.7	%54.1
$\hat{f}$	%48.2	%51.2	%45
(P_1,P_2)	%62.1	%56.3	%58.1
$(\hat{f}_1,\hat{f}_2)$	%45.6	%62.9	%47.1
$(P_1,\hat{f}_1,P_2,\hat{f}_2)$	%71.6	%79	%68.9

5. CONCLUSION

SEMGs acquired from four muscles for five hand movements; finger flexion, wrist flexion, wrist extension, pronation,supination have been classified. SEMGs are segmented such that the center of the segment is the peak location of the SEMG channel with the highest average power. The three classifiers; linear Bayes classifier, Fisher' s linear discriminant and support vector machine are employed to distinguish the movements from the several combinations of features;the mean power, peak value of the envelope, the mean frequency of discrete Fourier transform and the estimated frequency by signal subspace method. Apart from the classical features, the use of the peak value and the estimated frequency by MUSIC method are introduced in this study. The Bayes classifier and peak value of the envelope feature set appear to be best in classification performance.

There are other studying involving the classification SEMG/EMG related to hand movement. Although the experiments of the studies are different and therefore comparison may not be appropriate, the performance some of the studies similar to this study is provided in Table (5.1). From the table it is seen that SVM classifier provides the best accuracy than the other classifiers and a close performance (93.7%) to those obtained by Oskoei and Huosheng is obtained. The accuracy is improved by the features classified with Bayes classifier to the maximum rate 99. 61%, while the highesty performance is 84% in the previous studies.

In Table (4.8)it is observed that the peak value and the mean frequency features provide better accuracy than the mean power and the estimated frequency by MUSIC method. Inter-subject classification performances of subject1 obtained by 4-fold cross validationwith Bayes classifier for the window size 512 provides best accuracy; %99.61 at maximum rate. It is also noticed that increasing the size of the training data improves the accuracy as it is expected. Also LDA and Bayes classifiers provide approximately the same results.

Because of the covariance problems in Bayes classifier when 2-fold cross validation method is used for classification we couldn' t investigate the accuracy for ($P_1, \hat{f}_1, P_2, \hat{f}_2$) segmentation; So we decided to use an SVM classifier as shown in

Table (4.11). The best accuracies are %93.76, %91.9, %88.15 for 512,256 and 128 samples respectively. These results belong to subject3.

In Table (4.16) we observe that by SVM classifier and using right hand data of a subject for training and left hand data of a same subject for testing, best and worst accuracies are %82.7 and %36.7 respectively. We also found that intra right hand subject and intra left hand subject classification performance has been quite poor (lower than 50%).

Table 5. 1.Previous studies

Study	Method	Performance		
		Min	Max	Average
Khezri & Jahed, 2007	Neuro-Fuzzy	%90	-	-
Zhi-zeng, Fei, & Ren-cheng, 2005	Bayes	-	%84	-
Zhao, Xie, Jiang, Cai, Liu, & Hirzinger, 2006	Wavelet Transform	%70	-	-
Ahsan, Ibrahimy, & Khalifa, 2011	ANN	-	-	%88.4
Marmara, Varol, & Yildiz, 2012	ANN	%83.45	%94.89	%89.26
	Diffusion Map Gustafson Kessel	%78.62	%84.35	%81.48
Yoshikawa, Mikawa and Tanaka 2006	SVM	%87	%92	-
Oskoei and Huosheng 2008	SVM	-	%95.5	-
	LDA	-	%94.5	-
Yi-Hung Liu, Han-Pang Huang and Chang-Hsin Weng 2007	CKLM	%93.54	-	-

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