DESIGN AND IMPLEMENTATION OF A DEVICE TO CONTROL A ROBOTIC ARM BY EMG SIGNAL

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ABSTRACT

DESIGN AND IMPLEMENTATION OF A DEVICE TO CONTROL A ROBOTIC ARM BY EMGSIGNAL

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In this study, an electromyogram (EMG)based human machine interface system is designed and implemented. System acquires EMG signals and processes them to generate commands to control a robotic arm. Different signal processing methodologies are investigated, realized, and compared.

The thesis study includes design and implementation of an 8 channels electromyogram data acquisition system which is used to record raw EMG signals from operator's muscles. The system transfers raw EMG data to control software via USB. Control software processes the raw EMG data accordingly and generates control commands which are used to control the robotic arm.

The robotic arm "AL5D" and its actuator driver which are used in thesis are not designed in the scope of this study. They are commercial products which are purchased from Lynxmotion Company. There are five servo motors placed on the robotic arm to realize movements. Communication with the robotic arm is achieved via USB so that the system may be interfaced with any PC.

In the near-real time implemented system, the operator is expected to contract his/her predefined muscles. Each muscle is used to control a specific servo on the robotic arm. After operator is trained to run the designed HMI (Human Machine Interface) system, he is able to drive the robotic arm with full functionality.

Different time domain and frequency domain signal processing algorithms are investigated in this study.However, only time domain algorithms are implemented in the designed near-real time HMI system. On the other hand, frequency domain algorithms are studied in post-processing environment. Time domain algorithms are based on different time domain features of the raw EMG signal.All time domain features aresuccessfully processed to drive the corresponding servo on the robotic armwith 100% accuracy.

Keywords: EMG, Human Machine Interface System, Robotic Arm

ÖZ

EMG SİNYALİ İLE ROBOT KOL KULLANIMI SAĞLAYAN CİHAZ TASARIMI VE ÜRETİMİ

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Bu çalışmada, elektromiyogram (EMG) tabanlı insan makine arayüzü (İMA) sisteminin tasarımı gerçekleştirilmiştir. Sistem EMG sinyallerini toplayıp işleyerek robot kolun kontrolü için gerekli komutları üretir. Çalışma kapsamında farklı sinyal işleme algoritmaları tasarlanmış ve karşılaştırılmıştır.

Bu tez kapsamında 8 kanallı bir EMG veri toplama sisteminin tasarımı ve üretimi yapılmıştır. Sistem kullanıcının kaslarından EMG sinyallerini toplar ve evrensel seri yol (USB) aracılığı ile ana yazılıma iletir. Ana yazılım ham EMG verilerini işleyerek robot kol için kontrol sinyalleri üretir.

Kullanılan "AL5D" robot kolu ve sürücüleri bu çalışma kapsamında tasarlanmamıştır. Lynxmotion firmasının profesyonel ürünleri olarak satın alınmışlardır. Robot kol üzerine yerleştirilmiş 5 adet servo motor bulunmaktadır. Robot kolun arayüz kontrol dokümanında tanımlanan komut formatları ana yazılım içinde gerçeklenmiştir. Robot kol ile haberleşme evrensel seri yol (USB) ile yapıldığından herhangi bir bilgisayar ile kullanılması mümkündür.

Yarı-gerçek zamanlı olarak çalışan İMA'da (İnsan Makine Arayüzü) operator önceden tanımlanmış olan kaslarını kasması gerekmektedir. Her kas, robot kol üzerindeki farklı bir servo motoru sürebilmek için kullanılır. Bir kullanıcı yeterince eğitildikten sonra, robot kolu tüm işlevselliği ile kullanabilmektedir.

Bu çalışma kapsamında çeşitli zaman ve frekans bölgesi sinyal işleme algoritmaları tasarlanmıştır. Yarı-gerçek zamanlı İMA'da sadece zaman bölgesi algoritmaları uygulanmıştır.Bu çalışmada, frekans bölgesi algoritmaları sonradan-işleme metodu ile uygulanmıştır. Zaman bölgesi algoritmaları ham EMG sinyalinin farklı zaman bölgesi özelliklerine dayanmaktadır. Bu zaman bölgesi algoritmaları ile servo motorlar %100 başarı oranı ile sürülebilmiştir.

Anahtar Kelimeler: EMG, İnsan Makine Arayüz Sistemleri, Robot Kol

To my family

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CHAPTER 1

INTRODUCTION

Limbs of human beings are the most important actuation mechanisms which turn ideas into practice. We all need our arms or legs to realize our ideas and ease our lives. Limbs are the secret heroes of human civilization because most of our physical interaction with our environment is achieved by means of our arms. The loss of a limb whether through congenital amputation, disease or injury is a traumatic experience for any individual. Not only physical limitations are placed on amputees' lifestyle but also psychological effects of amputation limit social interaction.Even though healthy people think that they will never lose their limbs, some diseases and accidents may end up with an amputation. There are several diseases caused by circulatory disorders andthey result with loss of a limb; such as diabetic or gangrene. On the other hand, accidents such as traffic, labor accidents, electric shock hazards, and terror attacks, use of guns, explosives, etc. may harm limbs seriously and limb function may be lost.

As technology advances, engineers become able to develop solutions to help amputees facilitate their lives. Human Machine Interface (HMI) technology may be used to help amputees interact with their environment or control devices[1], [2], [3]. A specific case of this broad concept is that control of a prostheticdevice that functions similar to lost limbs by using only Electromyogram (EMG) signals. In this kind of HMI systems, electrical activity of the muscles are acquired by a biopotential amplifier then processed and classified to generate simple commands to control the prosthetic device. Therefore, this technology allows patients, who lost one of their limbs, to control their prostheses by means of their remainingmuscles.This specific type of HMI system is called EMG driven HMI system, and the device controlled by EMG signals is generally a prostheticarm[4], [5], [6].

After developments in processing capabilities and dimensions of adequate electronics and electromechanics, lost limb functions are attempted to be replaced by powered prosthetic devices. However, main tradeoff in EMG Driven Systems is between functionality of the prosthetic device and its practicality. Therefore, researchers focused on either to develop new signal processing techniques for better estimation and classification algorithms or to design prosthetic devices with improved functionality.

1.1 Scope of the Thesis

This thesis study is composed of design and implementation of an EMG driven HMI system. Necessary hardware to acquire EMG data and required software which implements designed algorithms are realized. A commercially available robotic arm AL5D produced by Lynxmotion Company is adopted to mimic a prosthetic arm to demonstrate the operation of the developed system.After the acquired raw EMG data is processed, generated control commands are convertedto a form which is compatible with the control commands of the robotic arm AL5D. The processing techniques described and implemented in this thesis could be also applied to control other devices.

In this application, it is aimed to make an operator able to perform basic movements with robotic arm by using EMG signals generated in his/her muscles. Overall system works in an open loop manner and some training is required to improve control performance of an operator. In addition, operator should practice to learn response of the device to his/her muscle contractions. Although the system is technically designed as open loop, control loop is closed with visual feedback by the operator. Operator who runsthe system with a specific purpose, visually checks whether position of the robotic arm is as desired or not.

Muscle activity of operator is sensed by EMG data acquisition system and different signal processing algorithms are developed and implemented in this study.

1.2 Organization of the Thesis

This thesis is composed of two introductory chapters which describe HMI system architecture available in literature and HMI application realized in scope of this study. General definition and description of HMI systems and someinformation about physiological background of EMG driven systems are shared in Chapter 2. A brief description of HMI system realized in this study is also given in Chapter 2.

Technical properties of surface EMG signal are provided in Chapter 3. In addition, signal processing techniques implemented in this thesis are described and mathematical backgrounds of these algorithms are provided in this chapter.

In Chapter 4, the EMG data acquisition unit, which is designed in scope of this study, is described briefly. Details of analog circuit, digital circuit (including embedded software) and integration of hardware with main control software are shared in this chapter.

Chapter 5 provides results of proposed algorithms on two different data sets. In addition, performance analysis of each algorithm is made in this chapter. A detailed comparison between designed methodologies is also made in this chapter.

Finally, Chapter 6 summarizes all the work done in this thesis. Observations and experience gained during this work is shared. Future work planned on the thesis topic and possible improvements for a more robust design are provided in this chapter.

CHAPTER 2

HUMAN MACHINE INTERFACES

Human Machine Interface (HMI) systems are described in [7] as a discipline which aims to make humans control or communicate with computers or other devices by using bio-signals. Another method of controlling or communicating with a device is named as Brain Computer Interfacing (BCI)[7], [8], [9]. BCI architectures use bio-signals generated due to brain activity in order to control a device or a computer. Both HMI and BCI, collects and extracts information from bio-signals and interprets them to form control commands for a specific application. BCI Systems, as described in [8] uses only brain activity. Therefore, main difference between an HMI and a BCI system is that HMI systems use bio-signals generated in body rather than brain.

Disabled people may experience serious difficulty while using assistive prosthetic devices, or robots which has traditional user interfaces. HMI systems which are controlled by myoelectrical signals provide an opportunity for disabled people to use devices which facilitate their life [7], [10], [11].

In this chapter, information on general system architecture of HMI Systems and physiology of myoelectric signals are summarized. Detailed description of proposed HMI system and information about its usage is also provided in this chapter.

2.1 General Description of Human Machine Interface Systems

Architectures of Human Machine Interface systems are composed of four main parts as described in [6], [7], [12], [13], [14]. These four main stages are data acquisition, feature extraction, classification, and controller stages.

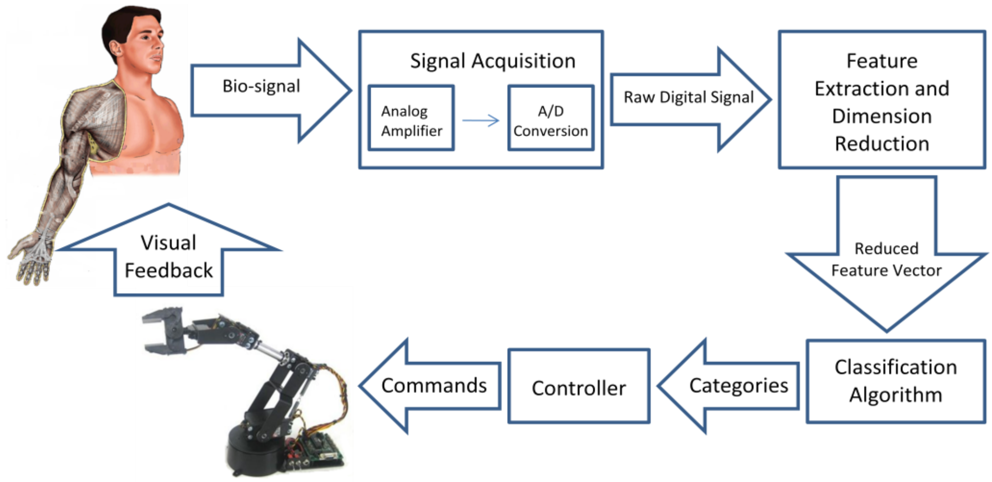

Figure 1: Architecture of a HMI System. Bio-signals are acquired from body by means of a signal acquisition unit, processed to form some feature vectors, and classified to generate control commands in a specific HMI System. (Body visual is taken from [15])

In signal acquisition stage, myoelectric signal is acquired from body and it is filtered in order to reduce artifacts and make signal band limited. Analog EMG signal is fed to an A/D converter and it is digitized for further processing by a computer. As a result, the digital signal, which contains information about electrical activity of the muscle, is fed to Feature Extraction Block.

In feature extraction stage, signal features, some of which are shared in [10], [6], [16], [11], [17], are extracted from the raw EMG signal and used to form feature vectors. These features of EMG signal may be classified in three groups as, time domain features, frequency domain features, and time-frequency domain features. Time-Frequency domain features are not studied in this thesis. Details of time and frequency domain features are provided in Chapter 3. Outcome of this stage is a feature vector which contains valuable information about contraction state of the sensed muscle. However, some redundant information may be included in this feature vector and some dimension reduction techniques may be applied to feature vector. The reduction techniques reduce the complexity of classification algorithm, as well.

Core of the HMI system is implemented in the classification stage in which the feature vector is classified to perform a predefined action. Different classification algorithms are available in literature [5], [7], [16], [18], [19], [20], [21], [22], [23], and performance of the HMI system depends on the accuracy of this stage. As categories are obtained more accurately, performance of the overall system is improved. Outcome of the classification stage is a decision on action to be performed.

In the controller stage, control commands generated and sent to the device which is desired to be controlled. This stage may alter as controlled device varies and different feedback mechanisms may be implemented. In general, HMI systems close the control loop visually. In other words, user has an audio/visual feedback and he/she drives the overall system accordingly. However, some of the HMI applications may need additional sensors like Inertial Measurement Units (IMU), to close the control loop [9], [24], [25], [26], [27].

2.2 Physiological Background about EMG Driven HMI Systems

As the name of the system implies, input of the EMG Driven HMI systems is myoelectric signal. In this part, physiological background of this signal is provided in detail and its measurement techniques are shared.

As defined in[16], bio-signal is a collective electrical signal acquired from any organ. These signals contain valuable information about physical variable of interest. On the other hand, EMG is a bio-signal which contains information about the electrical activity of muscles during contraction.

Neurophysiologic structure of the human body is responsible from EMG generation. Nervous system is both main controller and communication system[16], [28]. It controls muscle contraction and relaxation continuously and effects generated EMG signal.It is composed of three main parts: the brain, the spinal cord, and the peripheral nerves. Neurons are basic units of nervous system and their shape and size may vary with their place and mission in the nervous system. They are special cells which are responsible of conducting impulses from one point to anotherin the body.

Muscles are the main source of EMG signal. Muscle tissues are composed of bundles of muscle cells which are capable of contraction and relaxation. They make humans mobile and able to interact with environment. Even speaking becomes possible with existences and functionalities of these special cells. There are four main missions of muscle tissue: production of force, moving substance within the body (especially blood circulation), providing stabilization to the body, and heat generation. Muscles in the body may be grouped in three: skeletal muscles, smooth muscles, and cardiac muscles. The EMG signals in HMI applications are acquired from the skeletal muscles. These kinds of muscles are attached to skeleton and they provide support to the body and responsible from its movements. Contractions of skeletal muscles are voluntary. These contractions are initiated by the impulses arriving at neuromuscular junctions through neurons which are called "Motor Neurons". Smooth muscles are placed in the organs and they are not under conscious control. Finally, "Cardiac Muscle" is the muscle tissue which forms heart and it pumps blood through vessels around the body. Bio-signal which contains information about electrical activity of the heart is Electrocardiography (ECG) signal.

Motor units are constituted by the set of muscle fibers which are activated by one motor neuron [29]. When neuronal action potentials arrive at neuromuscular junction; muscle fibers contract and produce force and torque. In addition to contraction, action potentials are fired by this stimulation and they spread along the fibers. "Motor Unit Action Potentials"(MUAPs) are summation of these action potentials traveling through muscle fibers in a single motor unit[7]. Impulse trains create "Motor Unit Action Potential

Trains"(MUAPTs) in muscle tissues[7], [21], [30]. Since theMUAPTs are independent from the stimulation train, they can be treated as stochastic processes.

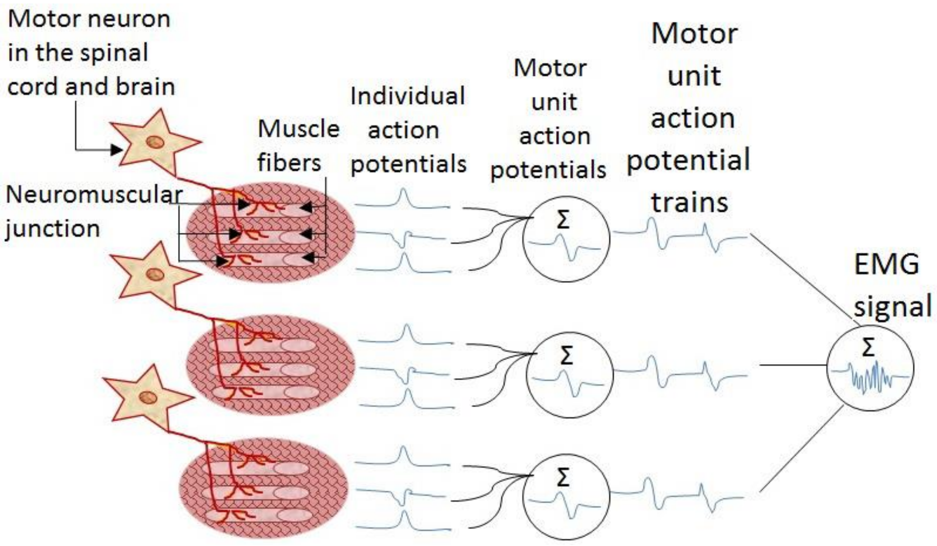

Figure 2: EMG Signal Generation Process[7]

Surface EMG signal is superposition of these MUAPTs. As a result, during processing of EMG signal, it may also be treated as a stochastic process. EMG generation process is provided in Figure 2.

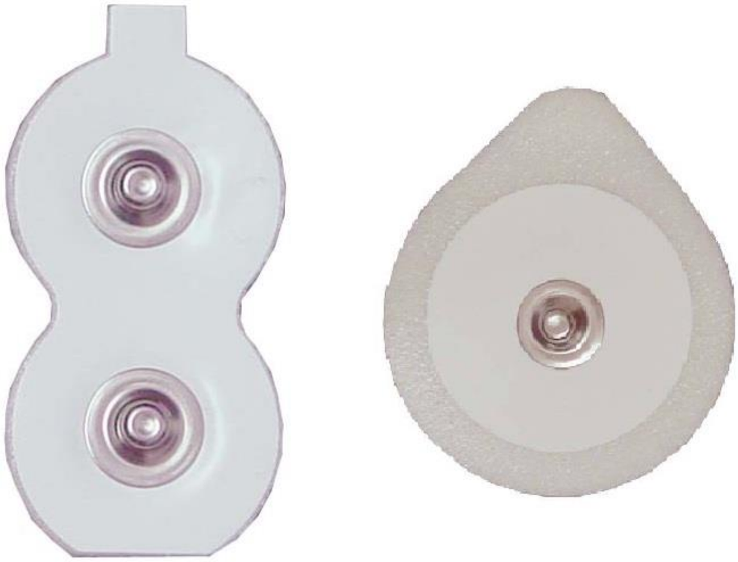

Figure 3: Ag-AgCl Surface EMG Electrodes

There are two ways of obtaining EMG signal from a muscle tissue: Invasive EMG Measurement Techniques and Non-Invasive EMG Measurement Techniques. Non-Invasive

EMG measurement is realized by surface EMG electrodes which are placed on skin surface on a muscle tissue.Obtained EMG signal is spatial and temporal summation of MUAPTs which are generated in muscle under the skin and amplitude of surface EMG signal is around 1-5 mV. There is no invasive work done in this study and Ag-AgCl surface electrodes used in this thesis are shown in Figure 3. In invasive EMG data acquisition, Micro Needle Electrodes, which are produced by Micro Electro-Mechanic production techniques, are used. These needles are placed on muscle fibers to obtain individual action potentials on muscle fibers. Micro Needle Electrodes are shown in Figure 4.

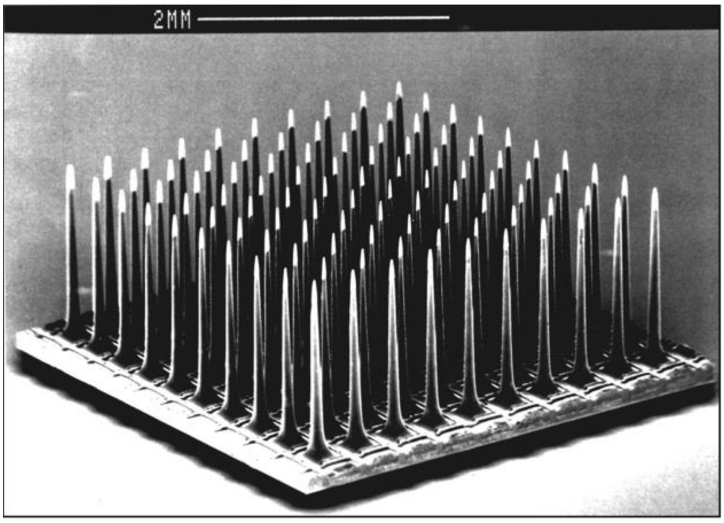

Figure 4: Micro Needle EMG Electrodes[31]

Although invasive EMG sensing is more painful compared to non-invasive sensing, it has more spatial resolution and gives more information about individual action potentials of each muscle fiber. There are works in literature about decomposition of surface EMG signal to its MUAPTs in order to decrease dependency on invasive EMG sensing [16].

An example of raw EMG signal,which is recorded from biceps brachii muscle with a surface Ag-AgCl electrode and proposed data acquisition unit, is given in Figure 5.

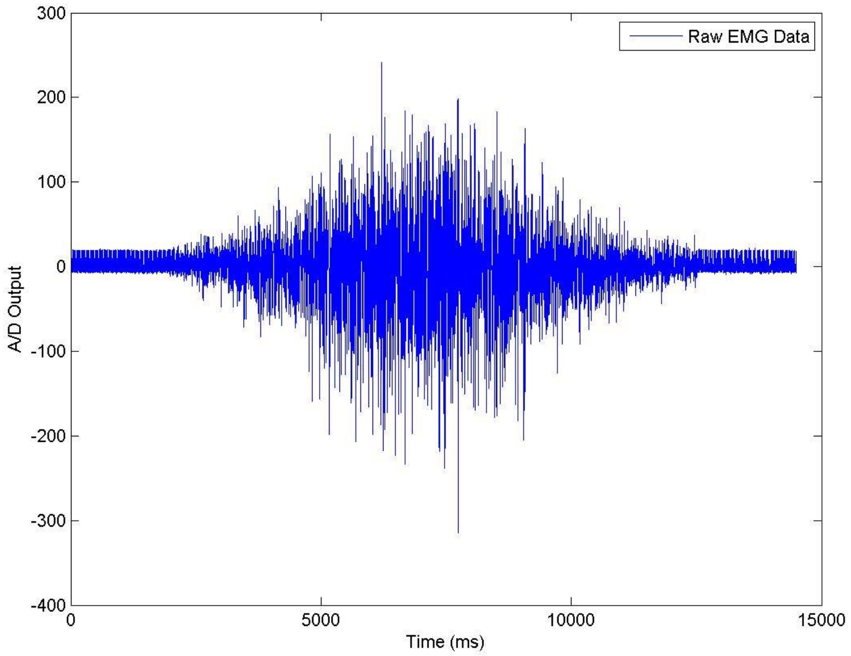

Figure 5: Raw EMG Signal Collected From Biceps Brachii with Proposed Data Acquisition Unit

2.3 Description of Proposed HMI System

As mentioned in the previous parts, although HMI systems have similar architectures, they may have some properties which are specific to the application. Detailed information about proposed HMI system in this thesis is shared in this section.

In accordance with the architecture provided in part 2.1, designed HMI system is composed of four main parts: data acquisition, feature extraction, classification, and controller.

Data acquisition unit is designed and implemented in this study, and its details are provided in chapter 4. It is composed of 8 isolated channels, and raw analog data is digitized at 1 KHz with a 10 bit A/D converter. As digital raw data is composed, it is transferred to computer via USB (Universal Serial Bus).

There are two different groups of work done in this thesis for feature extraction from raw EMG signal. First group is composed of near-real time implemented algorithms, and these algorithms are mainly designed to extract time domain features. The other group is the offline implemented algorithms which are designed to extract frequency domain features.

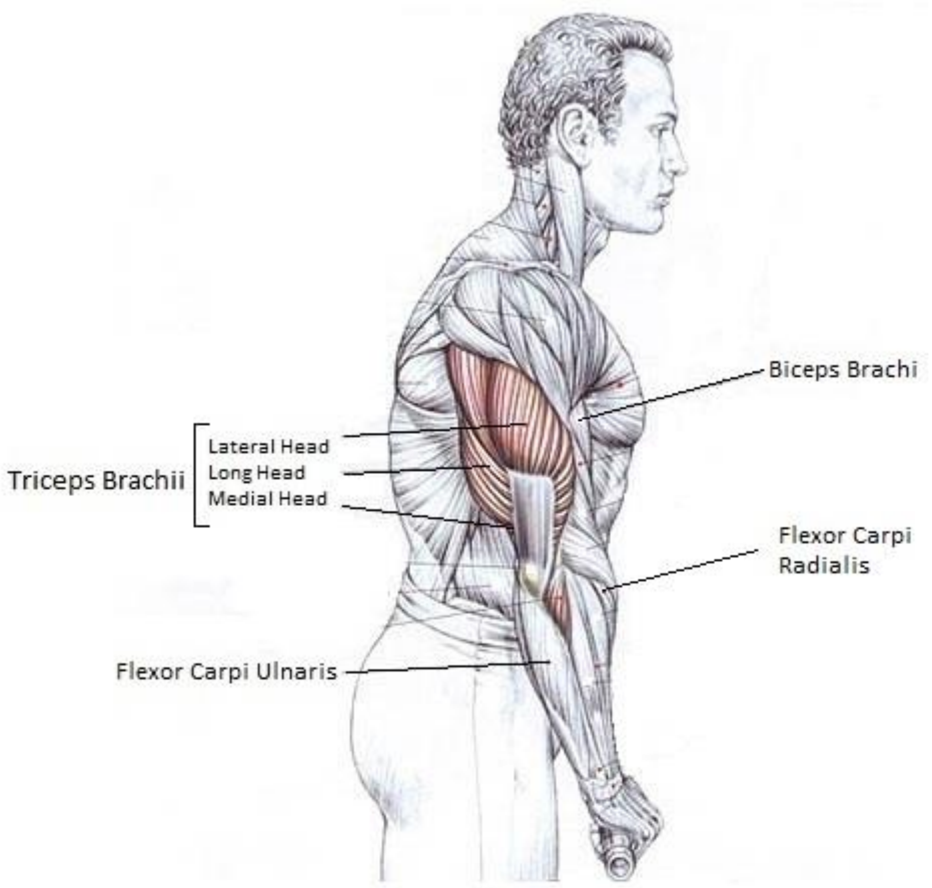

Figure 6: Muscles Used to Extract EMG Features in Operators' Arm[32]

Four different muscles per arm are used to extract EMG features and generate control commands for the robotic arm. These muscles are shown in Figure 6. Table 1provides information about matching between muscles and EMG data acquisition unit channels.Figure 7shows electrode placements on an operator's arms.

Table 1: Matching Between Muscles and Data Acquisition Unit Ch. Number

ARM	MUSCLE	DATA ACQUISITION CH. NUMBER
Right Arm	Triceps Brachii (Long Head)	CH#8
Right Arm	Biceps Brachii	CH#7
Right Arm	Flexor Carpi Ulnaris	CH#3
Right Arm	Flexor Carpi Radialis	CH#5
Left Arm	Triceps Brachii (Long Head)	CH#2
Left Arm	Biceps Brachii	CH#4
Left Arm	Flexor Carpi Ulnaris	CH#6
Left Arm	Flexor Carpi Radialis	CH#1

Figure 7: Electrode Placements on an Operator's Arms

Once the EMG acquisition channels are connected to appropriate arm muscles and control software is started on a computer to which acquisition device is connected, operator becomes able to drive the robotic arm. The operator is required to generate EMG signal at muscle tissue corresponding to servo that is desired to beactivated.

Raw EMG signals are processed for feature extraction and control commandsare generated for the robotic arm. In near-real time implemented algorithms, the formed feature vector is a one dimensional vector. Therefore, classification block shrinks to a simple threshold comparator. Another methodology for classification is to enlarge feature vector dimension and to detect different gestures. In this methodology, more individual classes may be distinguished with less independent data acquisition channels. HMI systems of this kind are called Gesture Detecting HMI systems. However, gesture detecting HMI systems, which control machines with less EMG data acquisition channels, have some drawbackswhen operated by disabled people. Since, amputees do not have a limb to perform predefined gestures; they may not be able to use gesture detecting HMI systems. On the other hand,amputees easily may run proposed HMI system with generating EMG signal at different muscle tissues without concerning gestures.Details of feature extraction block and classification block algorithms are shared in chapter 3.

CHAPTER 3

EMG SIGNAL PROCESSING TECHNIQUES

As described in chapter 2, the most important subsections of an HMI System are feature extraction and classification blocks. Signal processing algorithms which compose these blocks in the proposed HMI System are explained in this chapter. The chapter begins with a short description of raw EMG signal in terms of mathematical and statistical properties. It continues with description of how these properties are used as features and used for robotic arm driving purposes.

3.1 EMG Signal Description and Properties

Physiological background about generation of EMG signal in muscle tissue is shared in chapter 2. In this part, informative properties of EMG signal are shared. Methods to form feature extraction and classification blocks of the proposed HMI system are shared in the following part.

The EMG signal is a non-deterministic signal, which means that EMG signal cannot be represented by a differential equation[33], [16]. Stochastic nature of EMG signal prevents designer to use deterministic signal processing techniques in feature extraction block. Therefore, EMG signal should be processed by using statistical signal processing techniques. Properties of EMG signal may be grouped in three: time domain features, frequency domain features, and time-frequency domain features. All properties which may be found in related literature are shared in this part, except the time-frequency domain features, because they are not realized in scope of this thesis.

As mentioned in chapter2, raw EMG data, which is acquired from surface electrodes, are superposition of MUAPTs. In addition, high frequency components of these MUAPT signals are suppressed in tissue between muscle fibers and skin surface[7]. 95% of EMG frequency spectrum is up to 400 Hz. In proposed data acquisition unit, raw EMG signal is preprocessed in order to make it band limited. The acquired signal is first high pass filtered with cut-off frequency of 3 Hz and then low pass filtered with cut-off frequency of 500 Hz. Finally, in accordance with “Nyquist Sampling Theorem”, sampling frequency of proposed acquisition system is chosen as 1 KHz.

Firing of MUAPs' is random; therefore amplitude of EMG signal is also random. There is no mathematical definition which models acquired surface EMG signal. In such a condition, theory of stochastic processes is needed to be applied. There are some researches on statistical properties of raw EMG signal in literature to investigate that if the signal is Gaussian distributed or stationary[33]. Bilodeauet al. described that amplitude distribution of raw EMG signal has not normal distribution and may be assumed as stationary for a short period of time. In addition to these properties of EMG signal, study in[34]shows that not only amplitude of EMG signal is increased with increase of produced force or torque, but also mean frequency of the signal increases. Therefore, there are some frequency domain features which may be used in an HMI system.

In a real HMI applications, raw digital EMG signal flows with sampling frequency. In order to process raw signal, it is needed to be segmented. In literature, [18],[35], [36]describes two methods for segmentation of raw data in preprocessing: disjoint and overlapped segmentations. In disjoint segmentation, raw data is divided into non-overlapped segments of predefined length and these segments are used for feature extraction. On the other hand, in overlapped segmentation, new segment is created by sliding a window forward over current segment with a predefined increment. Sliding increment is also important in these applications. If it is longer than the segment length, some raw data remain unprocessed. In addition, if sliding increment is shorter than the processing time, queue of unprocessed data increase tremendously. As a result, sliding increment should be chosen between segment length and processing time. In the proposed HMI system, disjoint segmentation is used for segmentation and segment length is chosen as 50 samples which mean 50 ms at 1 KHz sampling rate. In addition to segmentation, at preprocessing level, mean of acquired raw signal is pulled down to zero. After, zero-mean segments are formed; they are processed for feature extraction.

In[10], [11], [7],[6], [13] both time domain and frequency domain signal features of EMG signals are investigated. These features are described in the following parts in detail.

3.1.1 TimeDomain Features of EMG Signal

In proposed HMI system; the EMG signal is amplified and digitized in time domain. As the name implies, time domain features of EMG signal are features that can be observed while signal is not transformed to another domain. Since there is no need for transformation, these features are obtained with less effort. In addition, algorithms extracting time domain features are easily embedded in real time (or near real time), standalone HMI systems.

All time domain features found in literature are shared in this part. In addition, their mathematical definitions are provided and they are extracted from a real test data.

1. **Integrated EMG (IEMG):** This feature is calculated by summing absolute value of samples of each segment of raw EMG signal,

$$IEMG_k = \sum_{i=1}^{N} |x_i| \tag{1}$$

where x_i is i^{th} sample of segment k. N is the number of samples in each segment. IEMG may be defined as discrete time integral of full-wave rectified raw EMG signal.

2. **Mean Absolute Value (MAV):** This feature is the mean value of absolute values of samples which form each data segment. In other words, raw signal is first full-wave rectified and then segmentation is done. Mean of each segment is the MAV of that segment. It is calculated as follows;

$$MAV_k = \frac{1}{N} \sum_{i=1}^{N} |x_i| \tag{2}$$

where x_i is the i^{th} sample of segment k and N is length of a segment. There are some variants of MAV in literature. As it is seen from equations (1) and (2), relation between IEMG and MAV is only scaling. Shapes of these features represented in Figure 9 and Figure 10 are the same; however a constant multiplier is needed to convert one to the other. In[37], and[19],two different weighting windows are applied in MAV calculation. Formulation of one of modifiedMAV calculation is as follows;

$$MAV_k = \frac{1}{N} \sum_{i=1}^{N} w_i |x_i| \tag{3}$$

where,

$$w_i = \begin{cases} 1, & if\ 0.25N \leq i \leq 0.75N \\ 0.5, & otherwise \end{cases}$$

In second modified MAV calculation, weighting window is improved and smoothed. Other proposed w_i in [37], and[19]is as follows;

$$w_i = \begin{cases} 1, & if 0.25N \leq i \leq 0.75N \\ \frac{4i}{N}, & if\ 0.25N > i \\ \frac{4(i-N)}{N}, & if\ 0.75N < i \end{cases}$$

3. **Mean Absolute Value Slope (MAVS):** This feature is simply discrete time derivative of feature MAV. It can be calculated as;

$$MAVS_k = MAV_{k+1} - MAV_k \tag{4}$$

4. **Root Mean Square (RMS):** It is defined as[11],[37], [19],

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \tag{5}$$

5. Simple Square Integral (SSI): This feature simply uses energy of the raw EMG signal and it is used as a feature[37]. It may be expressed as;

$$SSI_k = \sum_{i=1}^{N} |x_i|^2 \tag{6}$$

6. Variance of EMG (VAR): Variance is related to power of raw EMG signal[37]. Study in [38] uses instantaneous power of EMG signal in an HMI application.Since signal is zero mean in general, calculation of variance can be expressed as;

$$VAR_k = \frac{1}{N-1}\sum_{i=1}^{N} x_i^2 \tag{7}$$

7. Waveform Length (WL): Resultant feature is a measure of raw EMG amplitude, frequency and duration of EMG. Its calculation is given in [6], [11], [37] as follows;

$$WL_k = \sum_{i=1}^{N-1} |x_{i+1} - x_i| \tag{8}$$

In WL calculation, magnitude of difference between two consecutive samples is concerned and integrated. The magnitude of WL increases as force or torque generated by muscle being sensed increases. Therefore, EMG signal may be detected and well classified with this feature.

8. Zero Crossing (ZC): Itis number of times that amplitude of EMG signal crosses y-axis in a segment. In order to avoid from background noise, a threshold may be introduced instead of y-axis. In other words, instead of counting crossing of $y = 0$ axis, crossing of $y = T$ may be counted. There are three conditions that two consecutive samples x_i and x_{i+1}should satisfy to increase the count of zero crosses. These conditions are provided inTable 2. When one of the first two conditions and the third condition in Table 2 are satisfied, number of zero crossings is increased by one. ϵ is the threshold which is used for noise avoiding purpose. Number of zero crossings is approximate estimation of frequency domain features[37]. Although nature of the EMG signal implies that the number of zero crossings increases when it starts, this time domain feature is not sufficiently robust against background noise. Since, number of zero crossing give approximate estimation about median frequency of raw signal, there will be no significant change in number of zero crosses in case of 50/60 Hz noise. When EMG spectrum is concerned, 50/60 Hz is in frequency band which covers powerful frequency components of the signal. In order to decrease effect of background noise, threshold should be introduced as described before.In addition, acquisition system performance may significantly limit applicability of this algorithm.

Table 2: Conditions on Two Consecutive Samples that Increase Zero-Crossing Number

Conditions on x_i and x_{i+1}
$x_i > 0$ and $x_{i+1} < 0$
$x_i < 0$ and $x_{i+1} > 0$
$\lvert x_i - x_{i+1} \rvert \geq \epsilon$

9. Slope Sign Change (SSC): This feature is very similar to ZC and it gives approximate estimation about frequency domain features of raw EMG signal. It can be formulated as;

$$SSC = \sum_{i=2}^{N-1} \left[g[(x_i - x_{i-1}) \times (x_i - x_{i+1})] \right] \tag{9}$$

where,

$$g(x) = \begin{cases} 1, & if\ x \geq threshold \\ 0, & if x < threshold \end{cases}$$

Since SSC and ZC are focused on similar time domain features, effect of 50/60 Hz noise is similar for two algorithms, as well. However, some improvement on noise robustness may be achieved by simply choosing proper thresholds for both of the feature extraction methods.

10. Willison Amplitude (WA): This feature is a measure of difference between two consecutive samples. Number of case that this difference is larger than a defined threshold is counted in each segment.WA is directly related to firings of motor unit action potentials[11]. Its formulation is as follows;

$$WA = \sum_{i=1}^{N-1} f(\lvert x_i - x_{i+1} \rvert) \tag{10}$$

where,

$$f(x) = \begin{cases} 1, & if\ x \geq threshold \\ 0, & if x < threshold \end{cases}$$

When compared with WL, WA and WL are so similar and only difference between them is that WA does not focus on amount of the increment/decrement between two consecutive samples. It simply compares absolute difference of two consecutive samples with a predefined threshold and counts differences above the limit. Therefore, WA does not have direct information about amplitude of raw EMG signal whereas WL has.

Suitable thresholds for ZC, SSC, and WA depend on gain of the data acquisition system, after a short training, an appropriate threshold may be found.

11. Histogram of EMG (HEMG): During extraction of this feature, distribution of samples in each segment is calculated for a raw EMG data. Distribution of signal may be used as a feature and used in classification. As number of samples in higher amplitude bins exceeds a predefined threshold, EMG signal detection and classification of this feature may be done.However information extracted from histogram of a signal is not enough for many cases. Therefore, histogram is not investigated in this study.

Figure 9-Figure **18** give described time domain features which are calculated from raw data that is given in Figure **8**.

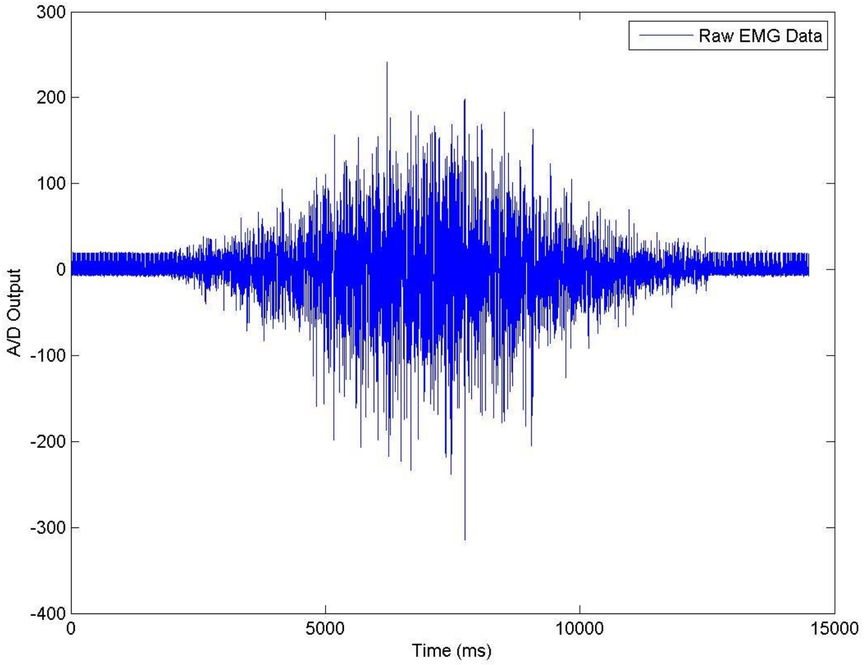

Figure 8: Raw EMG Data Used to Calculate Time / Frequency Domain Features

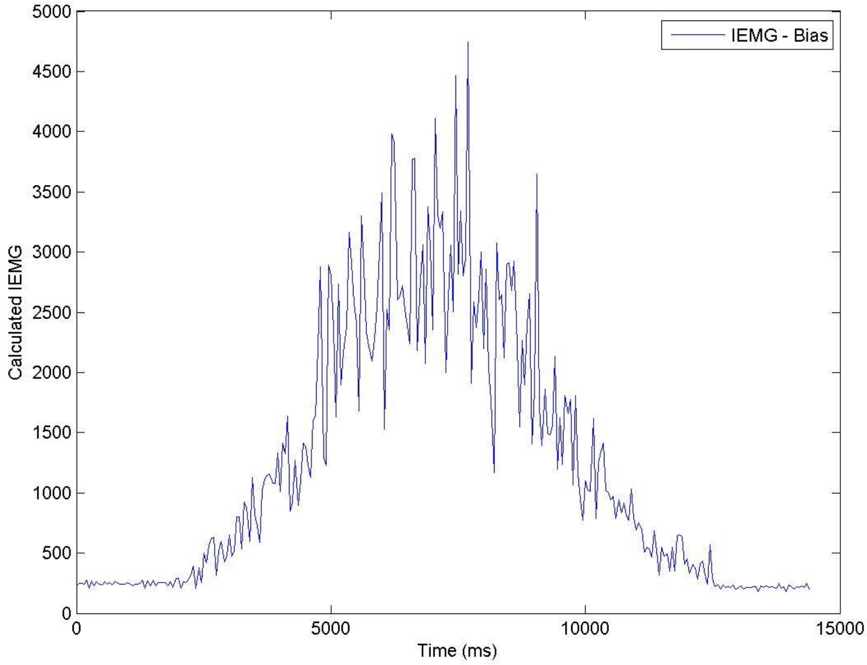

Figure 9: Integrated EMG Feature Generated with Window Length of 50 ms

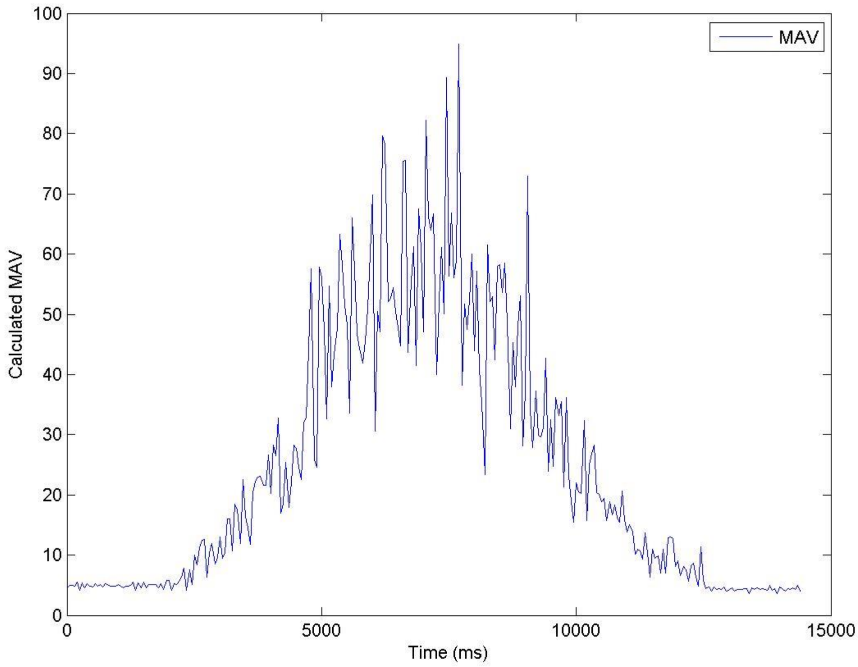

Figure 10: Mean Absolute Value Feature Generated with Window Length of 50 ms

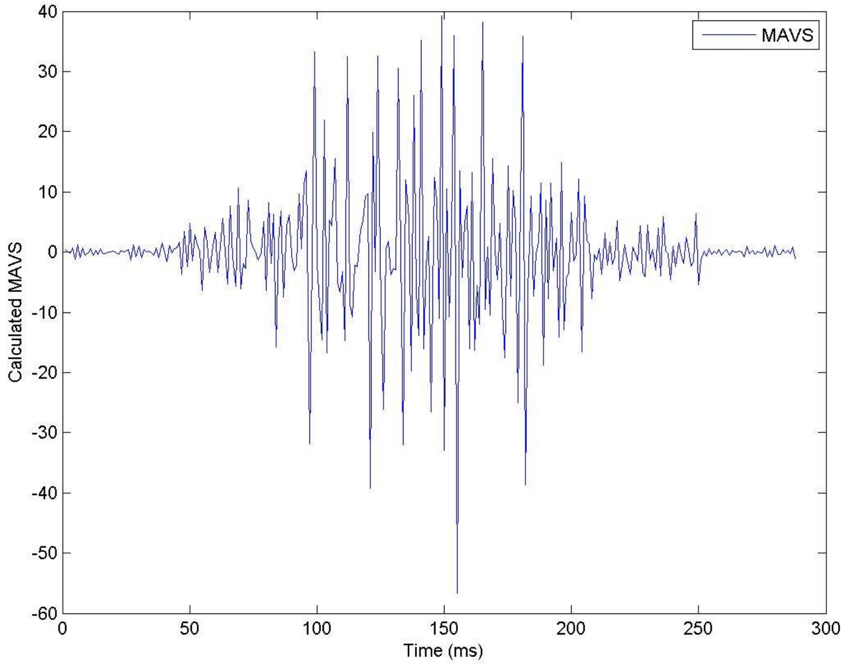

Figure 11: Mean Absolute Value Slope Feature Generated with Window Length of 50 ms

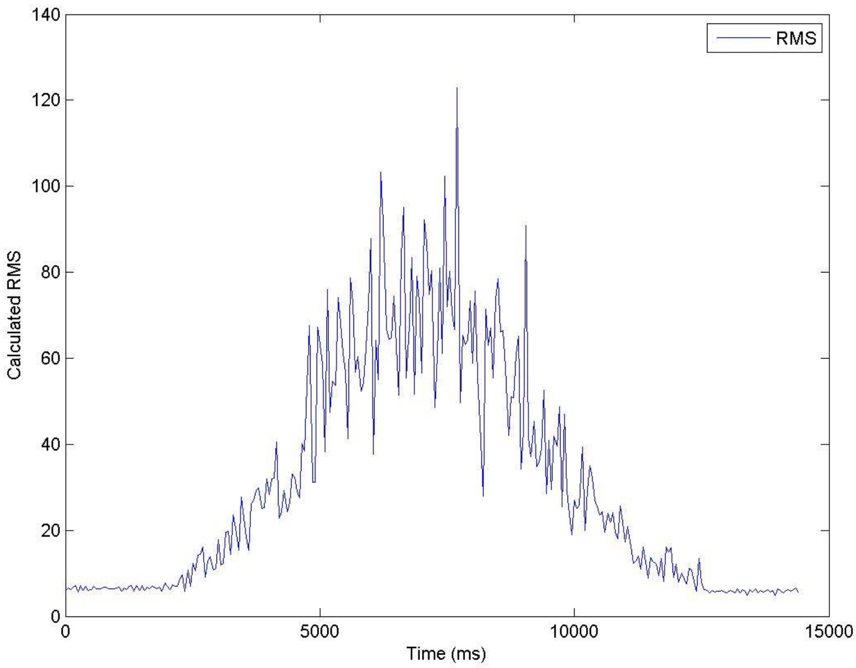

Figure 12: Root Mean Square Feature Generated with Window Length of 50 ms

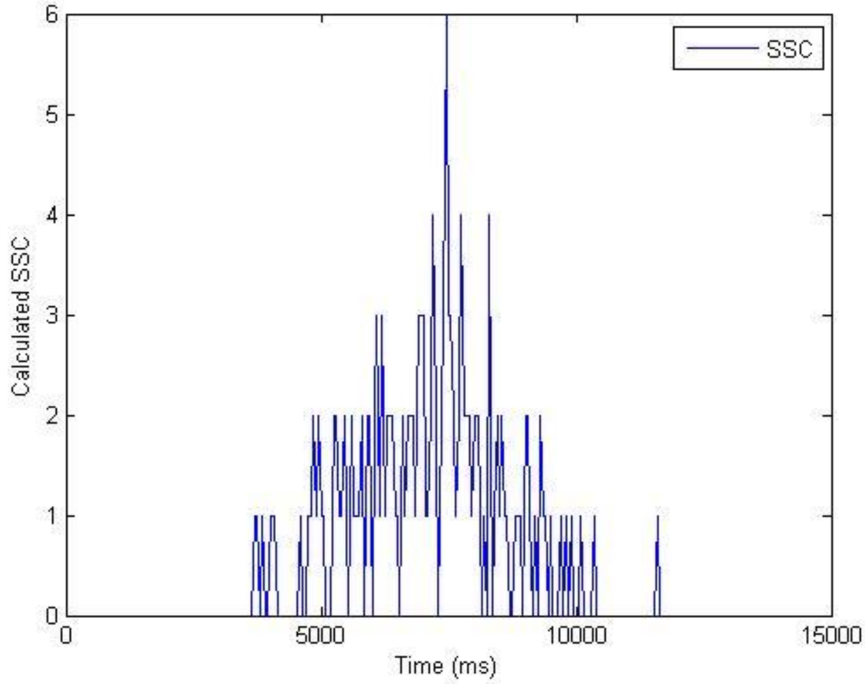

Figure 13: Slope Sign Change Feature Generated with Window Length of 50 ms

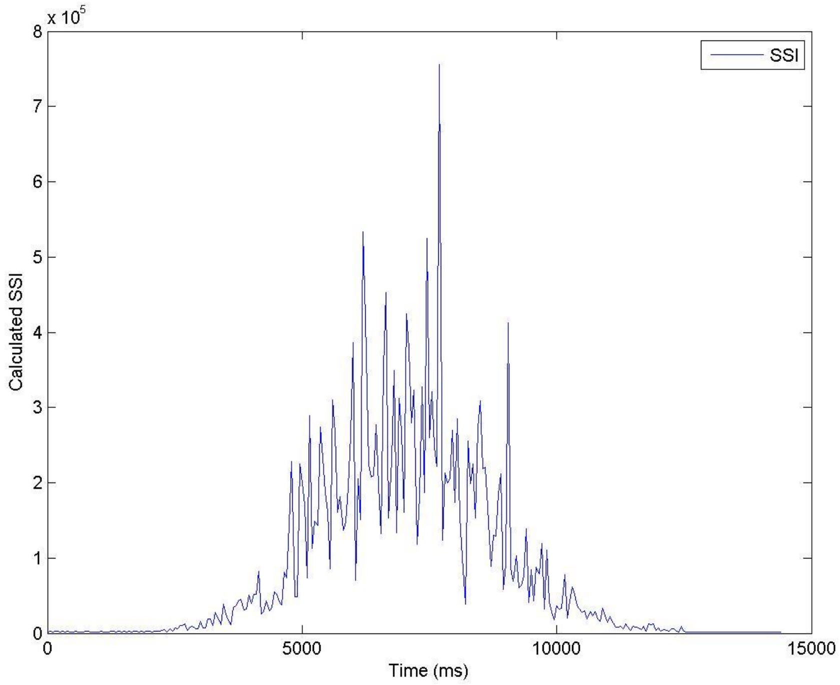

Figure 14: Simple Square Integral Feature Generated with Window Length of 50 ms

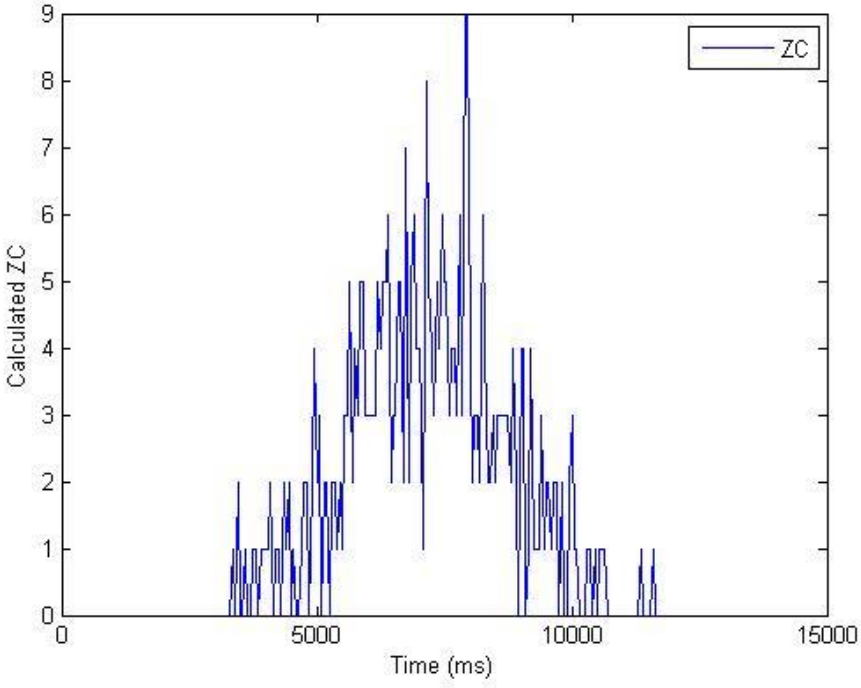

Figure 15: Zero Counts Feature Generated with Window Length of 50 ms

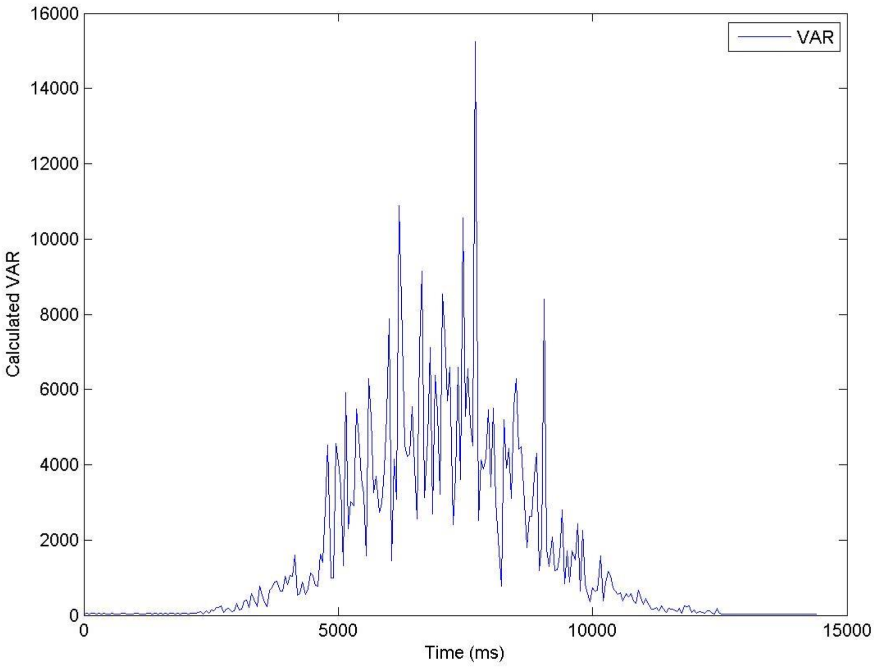

Figure 16: Variance Feature Generated with Window Length of 50 ms

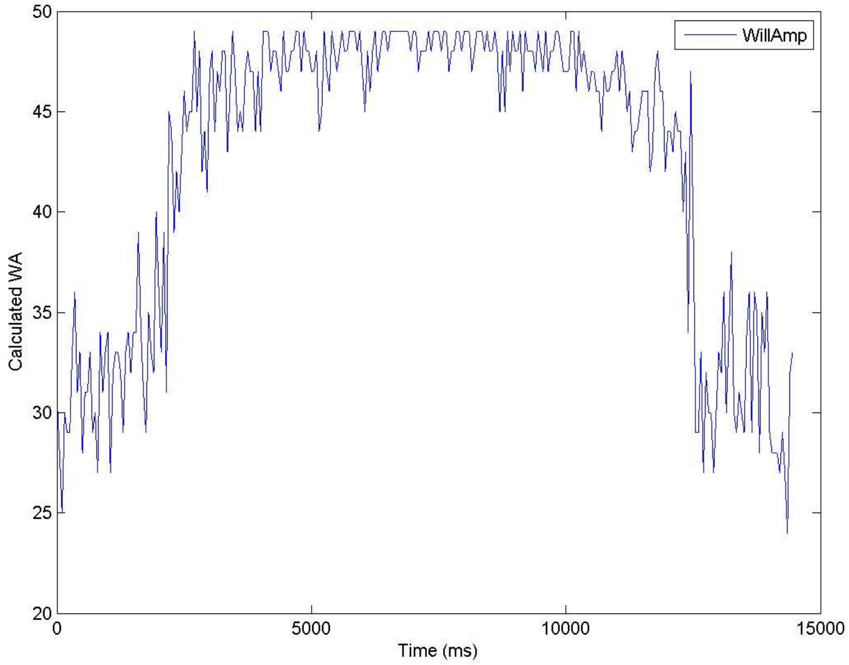

Figure 17: Willison Amplitude Feature Generated with Window Length of 50 ms

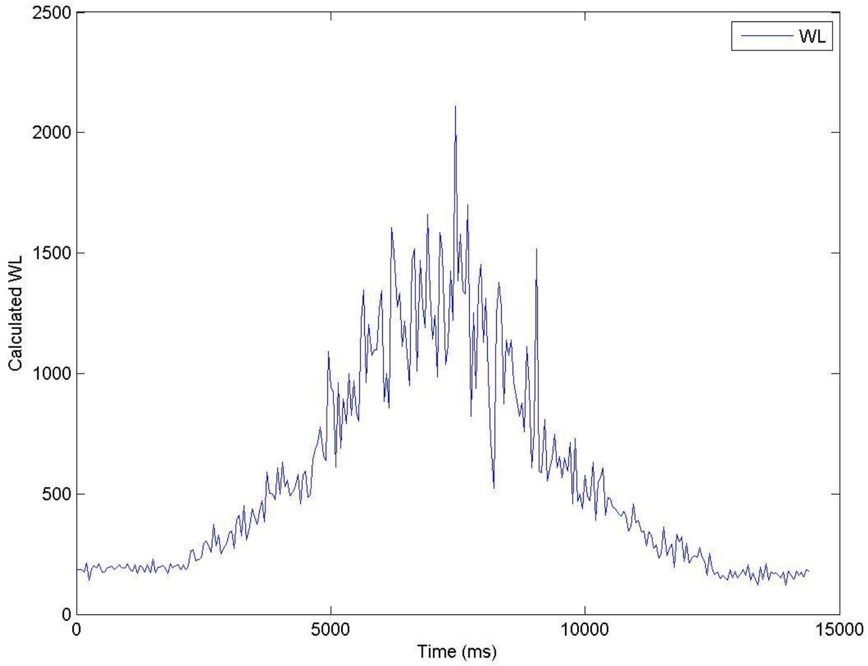

Figure 18: Waveform Length Feature Generated with Window Length of 50 ms

It is obviously seen that these time domain features may be used for EMG detection. In the proposed HMI system, simple threshold crossings may create “events” which is fed to classification stage. These events trigger the implemented controller. As mentioned before, time domain features directly affected form background noise which is due to both instrumentation and electrical environment in which experiment is realized. ZC and SSC features are most noise sensitive time domain features.

3.1.2 Frequency Domain Features

Another way of extracting useful features of raw EMG signal is to transfer it to frequency domain. As its power spectral density (PSD) or amplitude spectrum is calculated, some valuable information may be extracted for HMI purposes.

Frequency domain features are more robust to background noise than time domain features; however they are hard to be extracted from raw EMG signal. Study in [34] shows that some frequency properties of EMG signal varies with mechanical power or torque generated at muscle of interest varies. Therefore, these frequency parameters of the signal may be used in processing for feature extraction. Five frequency domain properties of EMG signal are investigatedin this part; Auto-Regressive Model Parameters, Frequency Median, Frequency Mean, Modified Frequency Median and ModifiedFrequency Mean. Descriptions of these features and details of study on extraction of frequency domain features are shared inthis part.

Most of the frequency domain features depend on calculation of power spectral density (PSD). In other words, power spectral density is used to distinguish EMG signals from each other and from the background noise. Figure 19 shows power spectral density of background noise of signal acquisition instrument designed in this study. Figure 20provides PSD of raw EMG signal which is given in Figure 8. When EMG signal is available, change in PSD of acquired signal may be seen asFigure 19 and Figure 20 compared.

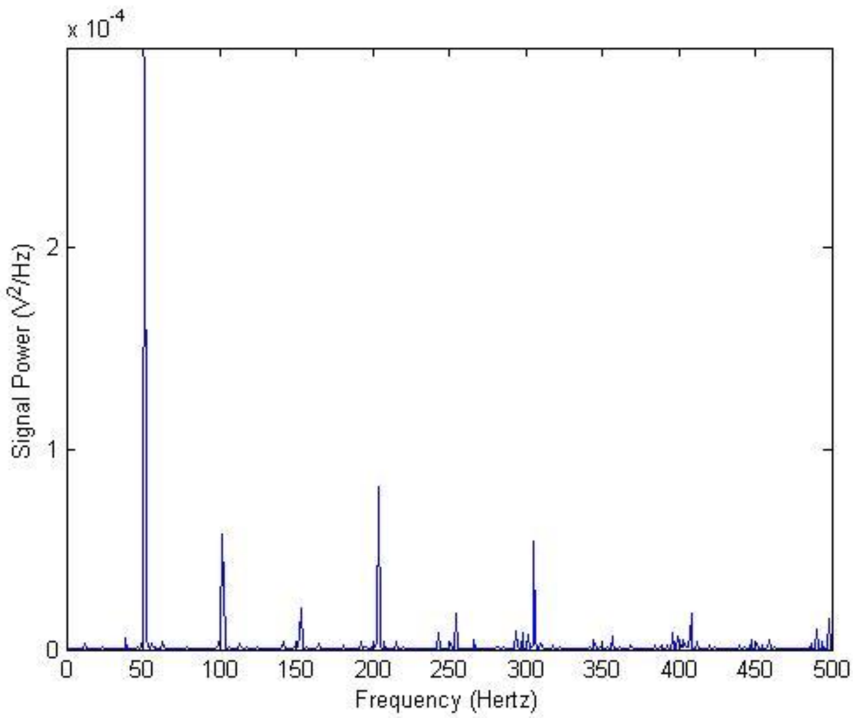

Figure 19: Power Spectral Density of Instrumentation Noise of Proposed Data Acquisition Unit

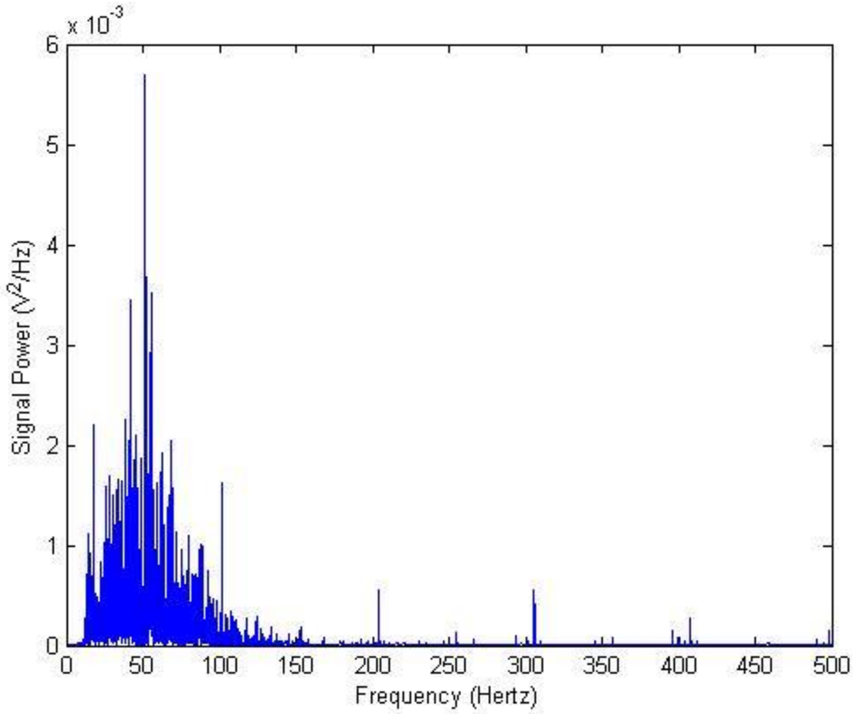

Figure 20: Power Spectral Density of Raw EMG Signal Given in Figure 8

Figure 19 shows that there is a dominating noise at 50/60 Hertz (50 Hertz in our case because line power in Turkey is distributed at 50 Hertz) in signal recorded while electrodes are attached to a muscle and the muscle is in idle state. In addition to main component around 50 Hertz, its harmonics are also seen on the background noise. As it is obviously seen, when EMG signal occurs, its main frequency lobe between 8 Hertz and 150 Hertz dominates calculated PSD.

Feature extraction blocks, which are based on frequency domain features, focuses on changes in PSD of raw EMG signal. It is observed that the ratio of frequency components of EMG signal and background noise at 50 Hz is 30. As a result, all frequency components of raw EMG signal are well differentiated from background noise.

Frequency domain features investigated in this thesis are shared below.

1. **Auto-Regressive Model Parameters (AR Parameters):** Thisfeature is based on Auto-Regressive Modeling technique which relates past samples to recentfuture sample.

$$y_k = \sum_{i=1}^{P} a_i y_{k-i} + w_k \qquad (11)$$

where a_i 's are model parameters, w_k is residual white noise and P is order of modeling. Details of AR modeling algorithm are provided in part 3.1.3.

2. **Frequency Median:** Median frequency is frequency which splits PSD into two equally powered parts. In other words, median frequency divides PSD into two parts that powers at two frequency bands are equal. Its definition is given in[7],[37],[11] as:

$$\sum_{j=1}^{MDF} PSD_j = \sum_{MDF}^{M} PSD_j = \frac{1}{2}\sum_{j=1}^{M} PSD_j \qquad (12)$$

where M is length of PSD and $PSD_j$is corresponding PSD value.

3. **Frequency Mean:** Its definition is given as average frequency in[7], [37], [11]. For better understanding, it is dominating frequency component or mean of all frequency components. It may be computed as:

$$MNF = \frac{\sum_{j=1}^{M} f_j PSD_j}{\sum_{j=1}^{M} PSD_j} \qquad (13)$$

wheref_j is frequency of spectrum in j^{th} frequency bin.In addition, unit of the ratio is Hertz.

4. **Modified FrequencyMedian:** Definition of Frequency Median shows that it is calculated by using PSD of EMG signal. In Modified Frequency Median calculation amplitude spectrum is used.It may be calculated as:

$$\sum_{j=1}^{MDF} A_j = \sum_{MDF}^{M} A_j = \frac{1}{2}\sum_{j=1}^{M} A_j \tag{14}$$

whereA_j's are corresponding values of amplitude spectrum.

5. **Modified Frequency Mean:** Similar to Modified Frequency Median, difference between Frequency Mean and Modified Frequency Mean calculations is that amplitude spectrum is used instead of PSD. Therefore, it may be calculated as:

$$MNF = \frac{\sum_{j=1}^{M} f_j A_j}{\sum_{j=1}^{M} A_j} \tag{15}$$

whereA_j is amplitude spectrum component, f_j is related frequency component, and M is length of amplitude spectrum.

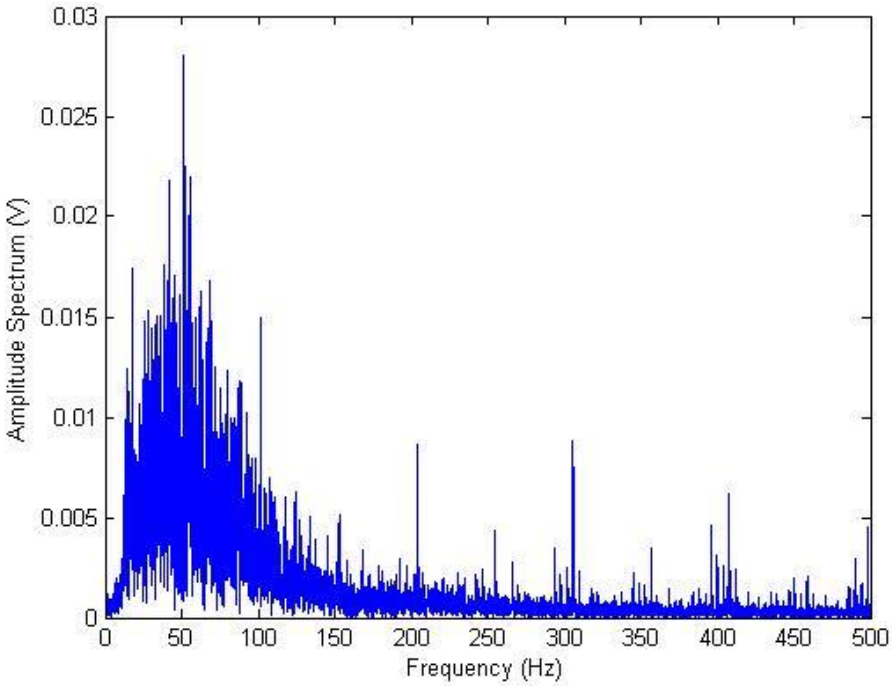

Figure 21: Single Sided Amplitude Spectrum of Raw EMG Signal

Single sided amplitude spectrum of raw EMG signal represented in Figure 8 is given in Figure 21. Frequency domain features, calculated by using PSD given in Figure 20 and amplitude spectrum given in Figure 21, are provided in Table 3.

Table 3: Frequency Features of Signal in Figure 8 and Instrumentation Noise

Frequency Domain Feature	Idle State	EMG Signal Available
Frequency Median	152.343750 (Hz)	54.260254 (Hz)
Frequency Mean	188.490483 (Hz)	62.832368 (Hz)
Modified Frequency Median	250.976562 (Hz)	71.960449 (Hz)
Modified Frequency Mean	247.798424 (Hz)	111.359112 (Hz)

As it is seen from Table 3, mean frequency and modified mean frequency varies in a larger scale and they are so suitable for classification algorithms. At absence of EMG signals, there are 50/60 Hz noise and its harmonics only. Therefore, mean frequency features of idle state are close to middle of whole frequency spectrum. When EMG signal shows up, these mean frequency features shifts to dominating frequency component of bio-signal.

On the other hand, when median frequencies are examined, these features are hard to change. It splits frequency spectrum to two equally powered parts.EMG signal seen in Figure 8 does not belong to an impulsive contraction. Therefore, frequency median for this signalisin low frequency band. As contraction becomes more impulsive, median frequency is expected to increase. The EMG signal shown in Figure 8 is record of biceps brachii muscle activity while 10 kg of weight is being ascended for five seconds, hold for fiveseconds, and descended for five seconds. As a result, both slow nature of force production and fatigueeffect creates a low dominating frequency. In an impulsive contraction case, median frequency and modified median frequency features may be calculated far from 50 Hz.

AR parameters are main frequency domain feature studied in this thesis. Calculation of these parameters is more complex.Some manipulations should be done to create necessary conditions for their calculation. Details of work done on AR modeling and AR parameter calculation are shared in part 3.1.3.

3.1.3 Auto-Regressive Signal Modeling

As mentioned in previous part, AR model parameters may be used as a signal feature. Once these parameters are obtained from segmented raw data, they are compared with AR parameters of a well-known movement. Therefore, gestures may be identified with AR parameters of raw EMG signals.

AR modeling is basically a random process modeling. In order to calculate AR model of a random process, an all-pole filter should be designed. When this filter is excited with white noise, output of the filter should be the random process which is desired to be modeled.

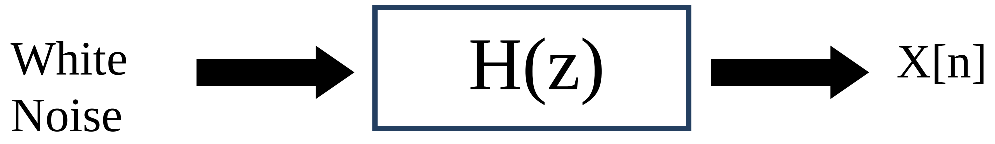

Figure 22: AR Modeling Structure

Transfer function, H(z) of this filter is in all pole structure and may be represented as follows:

$$H(z) = \frac{b_0}{1 + \sum_{k=1}^{P} a_k z^{-k}} = \frac{X(z)}{W(z)} \tag{16}$$

where, a_k's are the AR model parameters.

Yule-Walker equations explain relation between the AR parameters and auto-correlation sequence of the random process of interest. If equation (16) is transferred into time domain, we have equation (17) and (18).

$$x[n] + \sum_{k=1}^{P} a_k x[n-k] = b_0 \mathrm{w[n]} \tag{17}$$

$$x[n] = -\sum_{k=1}^{P} a_k x[n-k] + b_0 \mathrm{w[n]} \tag{18}$$

After equation (18)is derived, b_0w[n] term may be accepted as error term and Least Squares methods may be used to solve a_k's[11], [39], [17].In order to solve these AR model parameters, Least Squares method is applied to minimize squares of w_k's.

Equation (18) describes how to estimate future samples by using the past samples.In addition, it should be noted that the number of past samples used for estimation is order of the filter H(z). Therefore, order of AR modeling is an important decision to make for designer. In order to decide the filter order, auto-correlation sequence of random process should be investigated. Auto-correlation sequence of a random process is composed of correlation of random variableswhich form time indices of the random process. Equation (19)is mathematical definition of auto-correlation sequence of a random process x[n].

$$r[k] = E\{x[n]x[n-k]\} \tag{19}$$

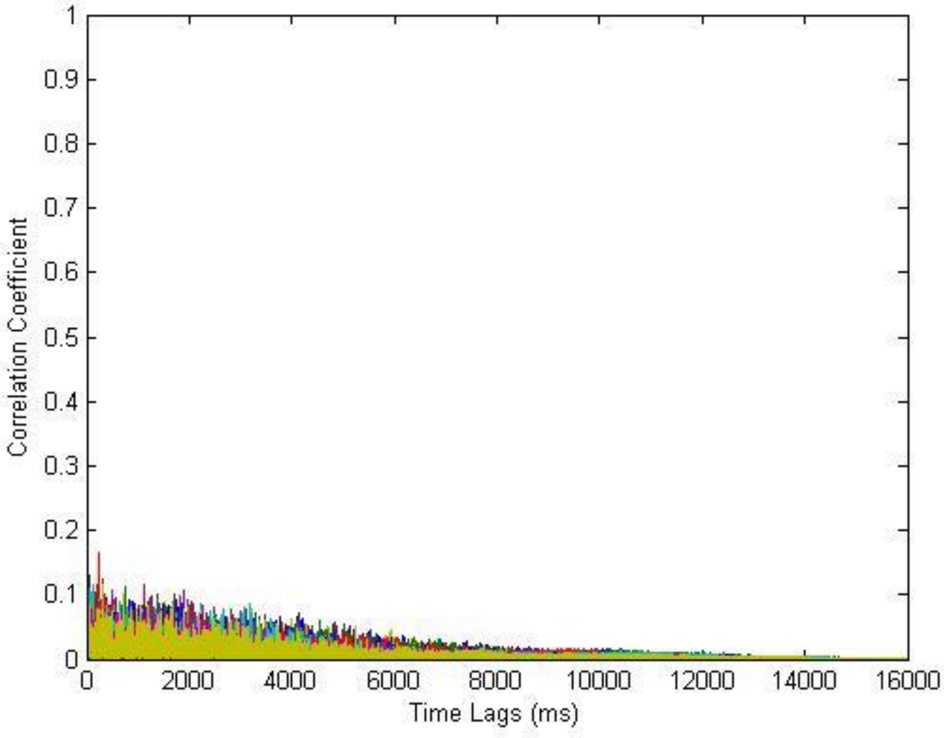

Figure 23: Monte Carlo Analysis of Correlation Coefficients of Raw EMG Signal

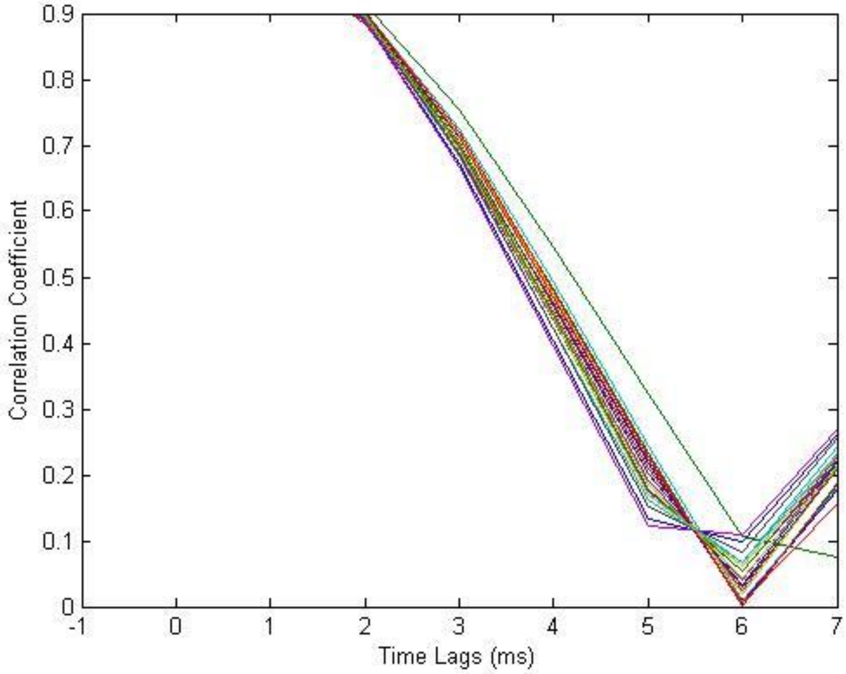

Figure 24: Zoomed Version of Figure 23

A Monte Carlo analysis of 50 runs is realized on correlation coefficients of different realizations of EMG generation process. Result of this analysis is shared inFigure 23 and Figure 24. As it is clearly seen, past samples may be thought as uncorrelated except 5 recentsamples, because correlation coefficients of $x[n]$ and $x[n-k]$ are very small for $k > 5$. As a result, in this study last 5 samples are used to estimate future samples. In other words, order of AR modeling realized in this thesis is 5.

$$x[n] = \sum_{k=1}^{5} a_k x[n-k] + \epsilon_n \tag{20}$$

Equation (20) represents time domain equation that is solved in AR modeling. $\epsilon_n$is the error term between $x[n]$ andestimate of $x[n]$and it is expected to be white noise. In order to find a_k's which minimizes ϵ_n's, least squares method is used[39].Study in[39], [40]shows that Recursive Least Squares algorithm (RLS) has the best performance between various least squares identification algorithms.Equations for RLS given in [41]are shared in equations (21)to(25).

System description is given as;

$$y_k = H_k \mathrm{x} + w_k \tag{21}$$

$$x_k^{est} = x_{k-1}^{est} + K_k(y_k - H_k x_{k-1}^{est}) \tag{22}$$

where; H_k is a row projection vector, and K_k is estimator gain matrix. Then equations of RLS estimation are as follows;

$$K_k = P_{k-1} H_k^T (H_k P_{k-1} H_k^T + R_k)^{-1} \tag{23}$$

$$x_k^{est} = x_{k-1}^{est} + K_k(y_k - H_k x_{k-1}^{est}) \tag{24}$$

$$P_k = (I + K_k H_k) P_{k-1} \tag{25}$$

where; R_k is $E\{w_k w_k^T\}$.

In order to apply Recursive Least Square algorithm for AR parameter estimation, equation (20)should be transformed into matrix form which is given in equation (26).

$$y_k = Y_k A_k + w_k \tag{26}$$

where; row vector $Y_k = \{\, y[k-1],\ y[k-2],\ y[k-3],\ y[k-4],\ y[k-5]\,\}$, andcolumn vector ofAR parameters$A_k = \{a_1;\ a_2;\ a_3;\ a_4;\ a_5\}$.

As we have equation (26), we can use recursive algorithm described in equations (21)-(25) to model raw EMG signal.

There are two remaining topics that should be mentioned in AR modeling; characteristics of residuals, and question of stationarity.

In discussion of stationarity, simplest way to evaluate stationarity of a signal is to examine physical phenomenon generating the signal. In surface EMG signal, instantaneous blood and oxygen supply to muscle is random; therefore surface EMG signal is not accepted as a stationary signal. However, the myoelectric activity of a muscle may be processed as it is stationary for short time periods (15~25 milliseconds)[39], [7].

Residuals are defined as the difference between original data and the estimated synthetic data. If fitting of AR model is adequate, residuals should be white noise as it is seen from Equations (16)-(18).

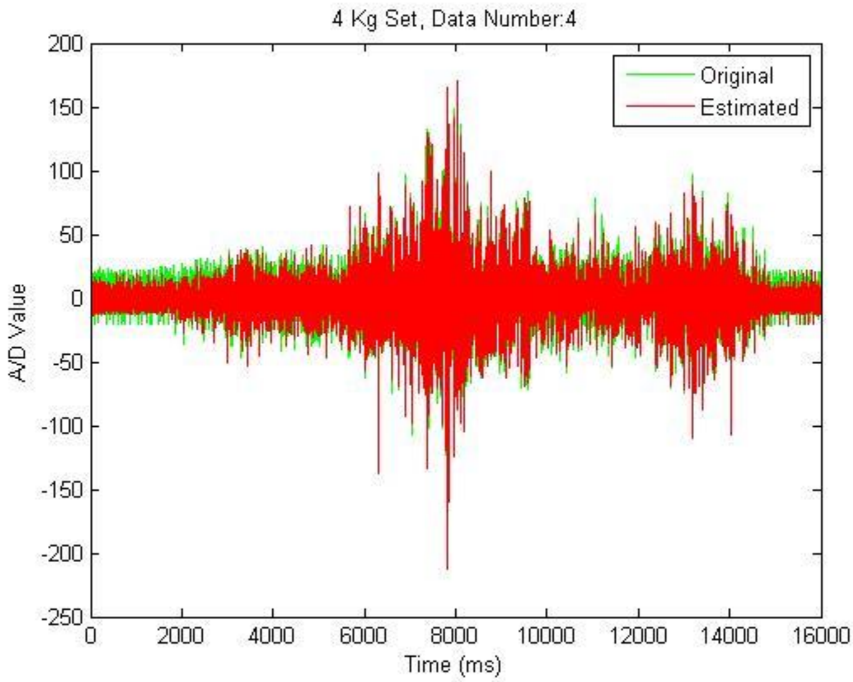

Figure 25: Estimated Surface EMG Data and Original Surface EMG Data

EMG signal acquired from biceps brachii during two different levels of contraction is shared in Figure 25. As it is seen, estimated signal fits the original one and residual of estimated EMG data is given in Figure 26.

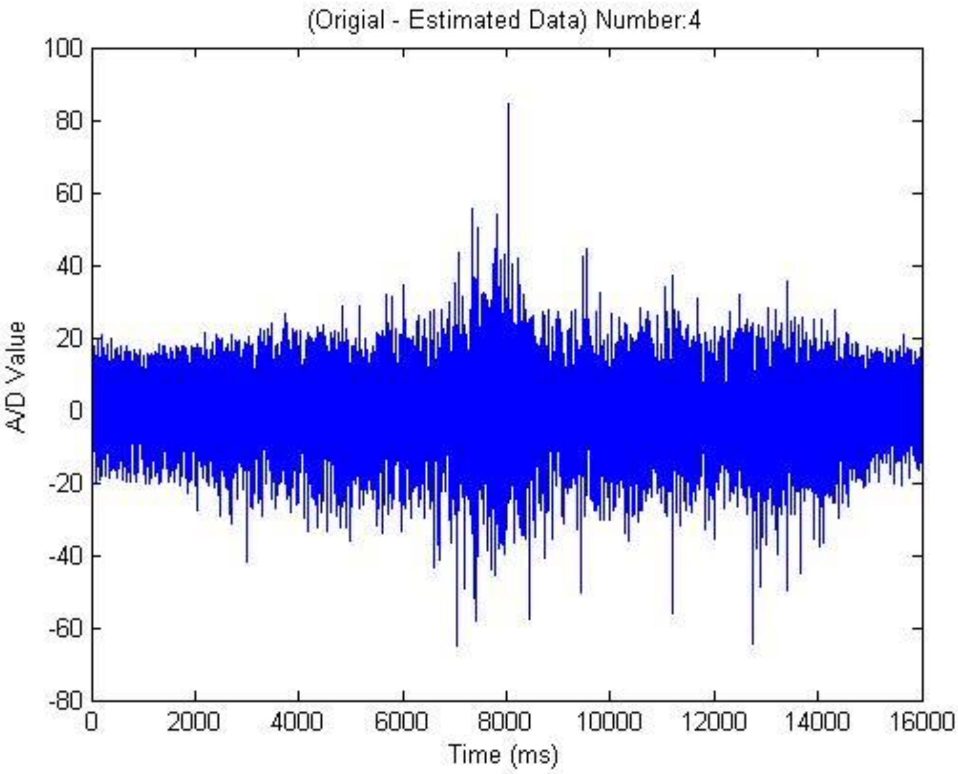

Figure 26: Residual between Estimated and Original Data in Figure 25

In order to clarify whether residuals are white noise or not, their auto-correlation sequences are calculated as defined in equation (19). By definition of white noise, it has zero mean and its auto-correlation sequence is in the form given in equation (27).Residual shared in Figure 26 has mean of -0.00625 which is practically zero.

$$E\{w_{t_1} w_{t_2}\} = \sigma_w^2 \delta(t_1 - t_2) \tag{27}$$

Equation (27) implies that each sample in a white noise is uncorrelated. In other words, autocorrelation sequence of a white noise is zero if time lag parameter is different than zero. However, due to correlated noise contaminations, autocorrelation sequences of residuals of a data set, that is given in Figure 27, is not exactly zero for time lags bigger than zero.

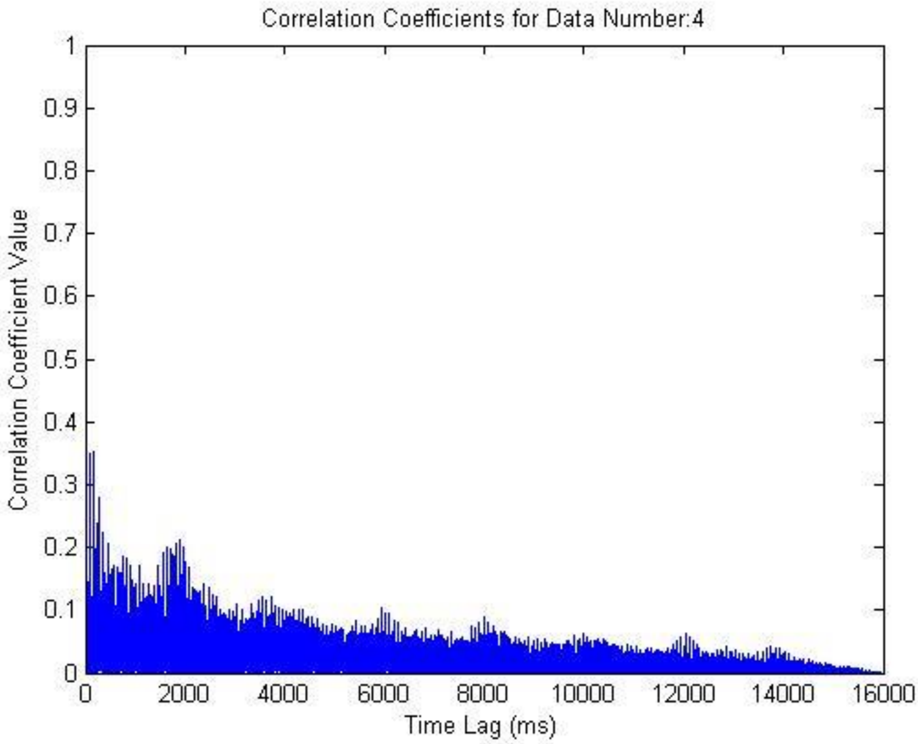

Figure 27: Correlation Coefficients of Residual given in Figure 26

Most powerful correlated noise coupled onto residual is 50/60 Hz noise. Local peaks separated at 20 ms time lags are due to 50 Hz noise on residual. In other words, estimation error on 50 Hz noise is observed on the autocorrelation coefficient sequence of residual. Except these local peaks, residuals may be accepted as a white noise, and AR parameters fit enough to model raw EMG signal.

3.2 Generating Control Commands by Using EMG Signal Features

As described in chapter 2, classification block follows the feature extraction block. In classification algorithm, time domain or frequency domain features are classified and one of the predefined categories are achieved. In addition to classification, action to be taken when the category is achieved is fed to controller block. In this part, methodology of classification is provided.

First description of Support Vector Machines (SVM) algorithm is described and then information on how SVM classification is applied to time domain and frequency domain features is provided.

Finally, methodology that produces control commands from output of classification algorithm is described.

3.2.1 Application of Support Vector Machines Classification Method

In Support Vector Machines (SVM) classification algorithm, a feature vector of dimension "n" is classified by using knowledge of a set of feature vectors and their category. In other words, a present feature vector is compared with other feature vectors of different classes and a classification is realized.

Visualization of two dimensional feature vectorsand separating hyperplanesmay be seen in Figure 28.

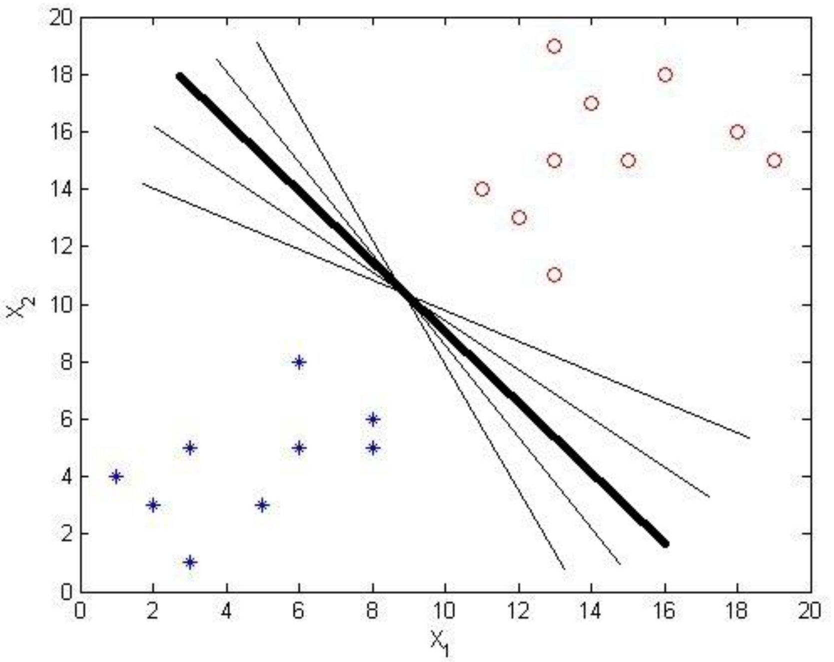

Figure 28: Visualization of Two Dimensional, Two Classes Classification

There are infinitely many hyperplanes separating these two classes. However, one optimum hyperplane may be found separating with maximum margin. In other words SVM algorithm tries to maximize distance between separating hyperplane and nearest sample of each class.

Once this hyperplane is found, each feature vector is compared with this hyperplane and decided its category. For instance, in the case shared in Figure 28, if feature vector being examined falls into space that is reserved for '*' class, it is categorized as '*'.

If the interested feature vector is two dimensional, hyperplane shrinks to a line. In addition, if interested feature vector is one dimensional, separating hyperplane becomes a point. In other words, the feature is simply compared with a threshold and if threshold is exceeded, an event is created.

In this study, time domain features are used to recognize whether sensed muscle is contracted A one dimensional time domain feature vector is calculated for each segment and compared with a predefined threshold. If the threshold is exceeded, the muscle is recognized as contracted. This threshold is obtained after a short training. In proposed HMI system, as interested time domain features of a segment exceed the thresholds, decision on which servo should be driven is simply made. In addition, this recognition methodology is implemented in near real time system due its simplicity.

Most of the works on frequency domain features are focused on AR model parameters. They are used as feature vectors and different arm movements are recognized by using SVM.Two movements are performed with 4 Kg and 10 Kg holding. As mentioned before, raw signal is segmented by disjoint segmentation method and AR model parameters are calculated for each segment. Therefore, AR parameters for each segment are used for recognition. AR parameters for two different data sets are shared in Figure 29 and Figure 30.

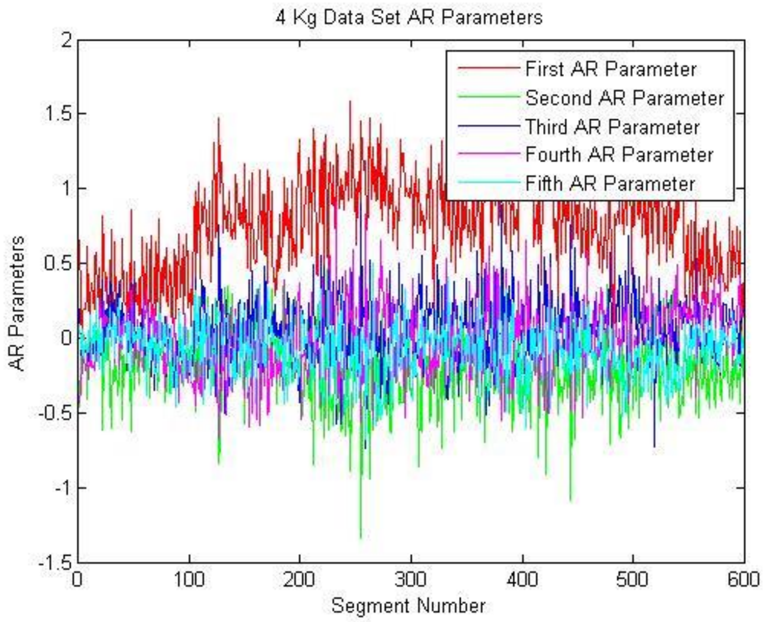

Figure 29: First AR Parameter of a Raw Data from 4 Kg Data Set

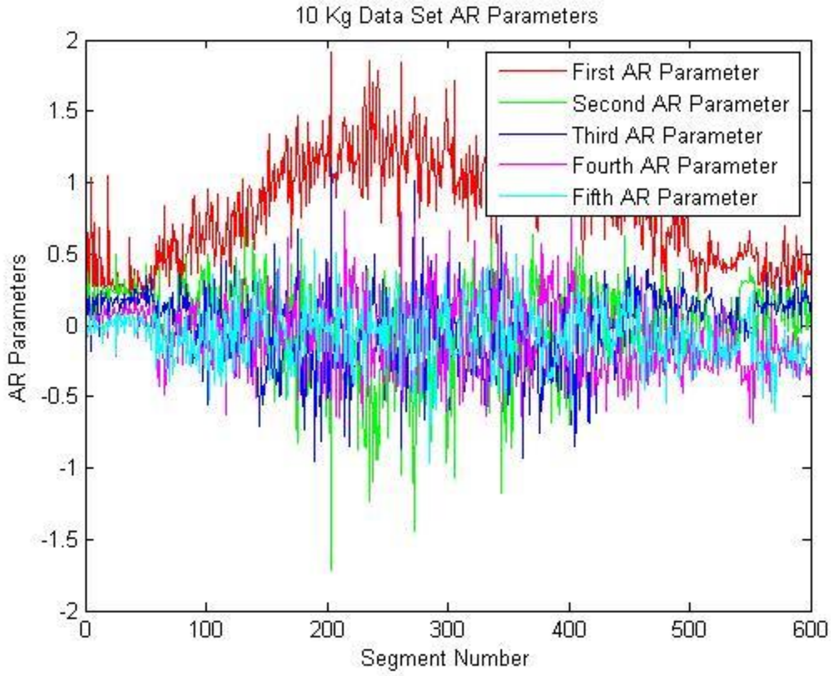

Figure 30: First AR Parameter of a Raw Data from 10 Kg Data Set

As seen from Figure 29 and Figure 30, the first AR parameters of two different data setsare distinctive enough for recognition of the arm movements. AR parameters are calculated and theyare processed forrecognition in post processing signal processing environment.

Details of results about both time domain features and AR modeling parameters are shared in chapter 5.

3.2.2 Generating Control Commands for Robotic Arm

The final goal of proposed HMI system is to drive the robotic arm AL5D. To control the robotic arm, only time domain features are used and embedded inthe realized nearly real time system. During normal system operation, data flow is segmented and a time domain feature is extracted for each segment. As these features create events, controller block is triggered and robotic arm is moved accordingly.

As it is mentioned before, robotic arm and its servo controller is purchased as commercial products. As a result, communication between robotic arm and main software is done via controller that is supplied with it.In addition, command message format, which is defined in Interface Control Document (ICD) of AL5D controller, is used in main software of proposed HMI system.

Electronic controller of AL5D expects two inputs in its commands. Information about position inputs and time required to perform the command for each individual servo should be sent to controller. Position limits of each individual servo are coded in main software to form a mechanical limit for reaching capability of overall system.Therefore, generated position orders for robotic arm are limited between these servo limits. In order to generate a new servo position command, current positions of each servo is memorized and instead of calculating its new position, a position increment is calculated. Once the increment and old position of the servo is known a new position order for that servo is computed and sent to controller unit.

For each segment of which feature is extracted and threshold is exceeded, position increments for related servos are kept constant. In other words, if raw EMG signal in a segment has feature to trigger position increment, a constant position increment is summed with old position of related servo and sent as a new position order. Constant position increment helps operator to learn responses of system while the operator is training.

CHAPTER 4

DESIGN OF EMG DATA ACQUISITION SYSTEM

Beside signal processing techniques in both feature extraction and classification blocks, mechanisms in measuring the muscle activity have also considerably important effect on overall system performance. Quality of EMG signal acquisition and recording device directly influences performance of HMI system algorithms. In this chapter, design of a prototype EMG data acquisition system is provided. EMG data acquisition system is composed of three main parts; non-invasive EMG sensing devices, analog and digital hardware, and main software controller. Design and implementation of these three main subsystems of EMG data acquisition system is explained in this chapter briefly.

4.1 EMG Design Requirements and System Specifications

- The most important requirement that any biomedical device should satisfy is electrical safety. In order to prevent operator from permanent harm, isolation from power network must be implemented properly.In order to achieve isolation from power line, isolated transformer and an isolated DC-DC converter is used in power supply circuit designed for analog circuitry.
- As it mentioned in chapter 2, amplitude of raw EMG signal is around 1-5 mV. Therefore, the data acquisition system is required to be able sense and record these signals. In other words, gain of analog amplifier should be arranged properly.In proposed prototype design of EMG data acquisition device, gain of the amplifier is chosen as 500. Therefore, amplified signal is kept in A/D voltage interval (0-5 V).
- Due to the fact that signal amplitudes are very low, environmental electrical noise affects signal quality easily. Therefore, EMG system should remove these noise components from the EMG signal.In proposed EMG system, in order to prevent noise imposed by power line common mode rejection ratio of the system is pulled up to 100 dB at 50 Hz.

- Resolution of analog to digital conversion should be considered during design, and quantization error during conversion should be kept as small as possible. On the other hand, data transfer speed between digital hardware and computer should be considered, as well. In addition to resolution, sampling rate at A/D conversion is also important.In order to make raw EMG signal band limited, analog filters are designed and implemented in analog amplifier circuitry. Components of raw EMG signal out of frequency band 3-500 Hz are suppressed. In accordance with Nyquist sampling theorem, sampling rate is chosen as 1 KHz to prevent aliasing in frequency domain. In addition to these, A/D conversion is realized with a 10 bits analog to digital converter (ADC).

- Number of channels should be enough to perform desired action with the device that is desired to be controlled.Since the proposed HMI system is used in a research and development study, number of channels of proposed EMG system is designed to be enough for each kind of system architecture. As a result, 8 channels are implemented in EMG data acquisition system.
- EMG system is responsible to feed all digital data coming from each channel to the main controller software without any loss.Digital circuit designed in this study transfers obtained digital data to main controller software via Universal Serial Bus (USB). During this transfer, a specific message structure is used to ensure no data loss occurs.

4.2 Analog Hardware

Analog hardware is composed of two main parts; power circuit and analog signal processing circuit. Power circuit is responsible to generate clean power signal which is supplied to analog circuit. Analog signal processing circuit is composed of amplifiers and active filters. It simply amplifies the raw EMG signal and filters it. Details of these circuits are explained in this part. Circuit schematics of these parts may be found in APPENDIX A.

4.2.1 Power Circuit

Power circuit mentioned in this part is the circuit which is responsible of supplying required electrical power to analog circuit. It has no connection to digital circuit in which the A/D conversion is done.

Output of the power circuit is ± 12 Volts DC at 9 Watts of power. ± 12 Volts is fed to operational amplifiers and instrumentation amplifiers in the analog circuit, therefore noise level of these output voltages should be kept very small under a proper load. Another requirement that this powering circuit should satisfy is that this circuit must be isolated from power line in order to prevent electrical damage to operator.

Power circuit is designed to operate under line voltage of 220 Volts at 50 Hz. In first stage of this circuit, an isolating transformer is used which reduces 220 Volts to 24 Volts and capable of supplying 9 Watts of power. This transformer produces a voltage source isolated from power line. Once 24 Volts sinusoidal power signal is obtained, it is full-wave rectified with a bridge rectifier and converted to a DC signal with a capacitor bank. As a result, 33 Volts DC power signal is obtained finally.

In the second stage of this power circuit, an isolating DC-DC converter is used in order to improve isolation and generate the necessary regulated output. Output at the DC-DC converter is ready to be fed to analog circuit as a power supply. Power circuit can be seen in Figure 31.

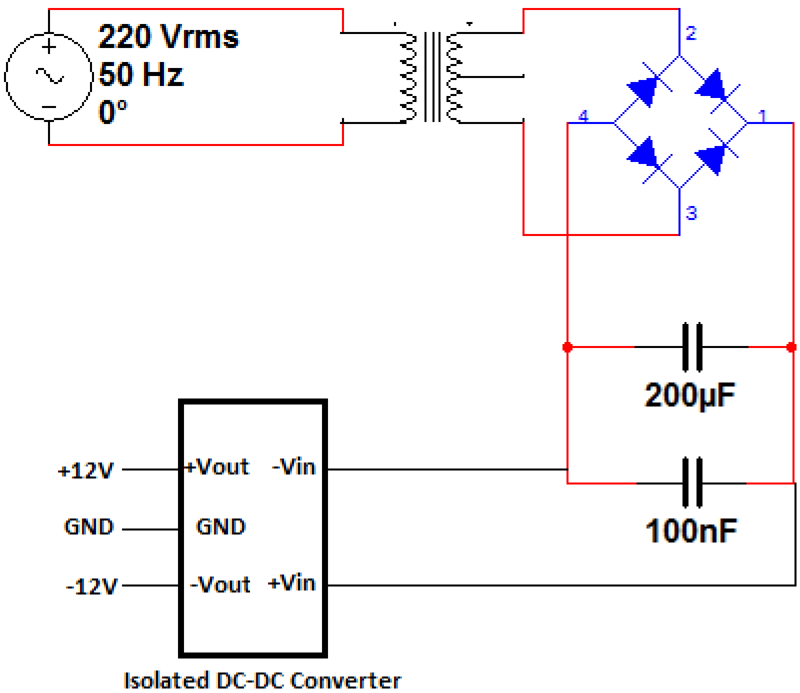

Figure 31: Power Circuit Schematics

4.2.2 Analog Signal Processing Unit

Analog signal processing circuit is designed to amplify signal which is obtained from surface EMG electrodes. In addition, active filters in analog circuit suppress the unrelated frequency components of the acquired signal. This circuitry is composed of three main parts; pre-amplification stage, low-pass filter, and high-pass filter.Circuit schematics of analog hardware may be found at APPENDIX A.

4.2.2.1 Pre-Amplification Stage

Pre-amplification stage is composed of an instrumentation amplifier (IA). This stage is expected to amplify small signals which are sensed at EMG electrodes. IAs have high common mode rejection ratio (CMRR) [42]which provides less noise contaminated signal at the output. These kinds of amplifiers are composed of two stages. In the first stage, a buffering is applied and common mode signal is reduced. Buffering in first stage is an important advantage for EMG applications, because it causes input impedance of amplifier to be very high. High input impedance prevents loading effect (Therefore, no current is drawn from signal source) at signal side that is desired to be amplified. In other words, since the EMG signal at skin surface is weak, buffering in the input stage transfers this weak signal to second stage. In the second stage of IA, there is a difference amplifier which amplifies the difference between two input signals.

IA topology consists of at least three operational amplifiers (op-amps) and matching of parameters of these op-amps has a considerable effect on performance. Therefore commercial integrated IAs in single package are available in the market. Since op-amps in these products are implemented on same wafer, their performances are much better than IAs implemented with individual op-amps. A commercial product AD620 of Analog Devices Comp. is used in this study. AD620 makes user able to set amplification gain with an external resistor, and no auxiliary elements are needed for operation.

4.2.2.2 Active Filters

The second stage of analog circuitry is composed of active filters. As mentioned before, these filters are used to make signal band limited and amplify the pass band frequency components of the raw signal. When gain at pre-amplification stage and active filters are considered, analog circuitry has an overall gain of 55 dB.

In proposed HMI application, 3~500 Hz frequency band is used in algorithms. Active filters are designed to amplify frequency components between 3~500 Hz. Active filters block is composed of high pass and low pass second order Butterworth filters. Butterworth filter is chosen due to its flat pass band characteristics. The magnitude and phase responses of these filters are shared in Figure 32 - Figure 35.

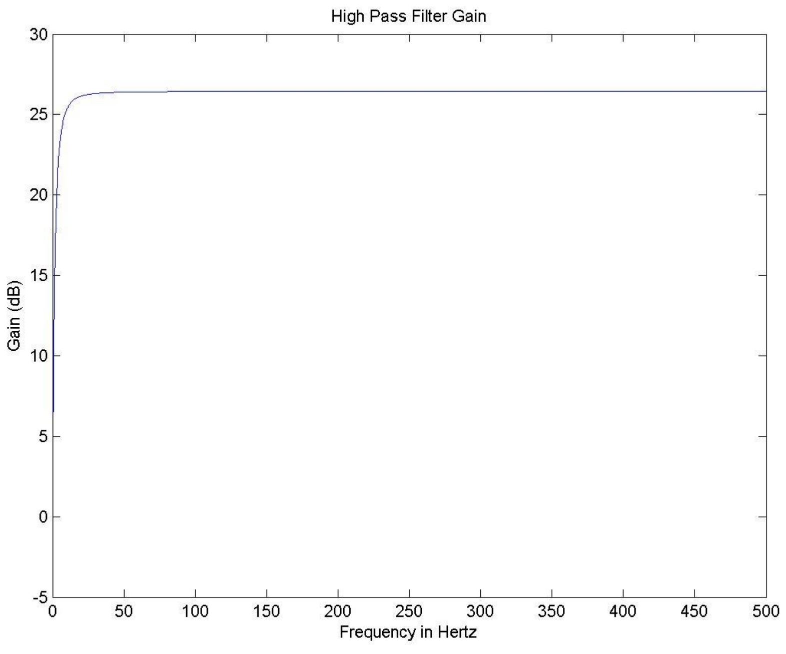

Figure 32: Magnitude Response of High Pass Filter in dB

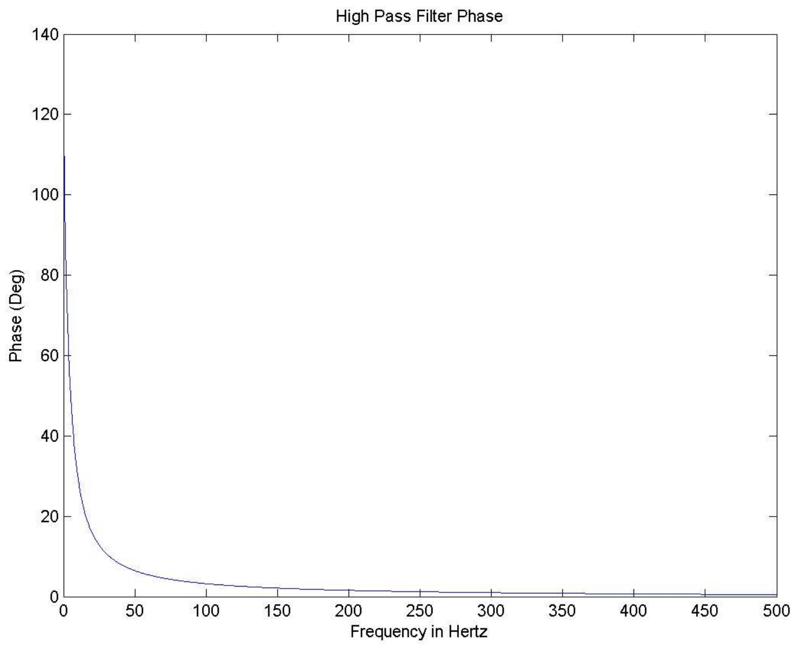

Figure 33: Phase Response of High Pass Filter in Degrees

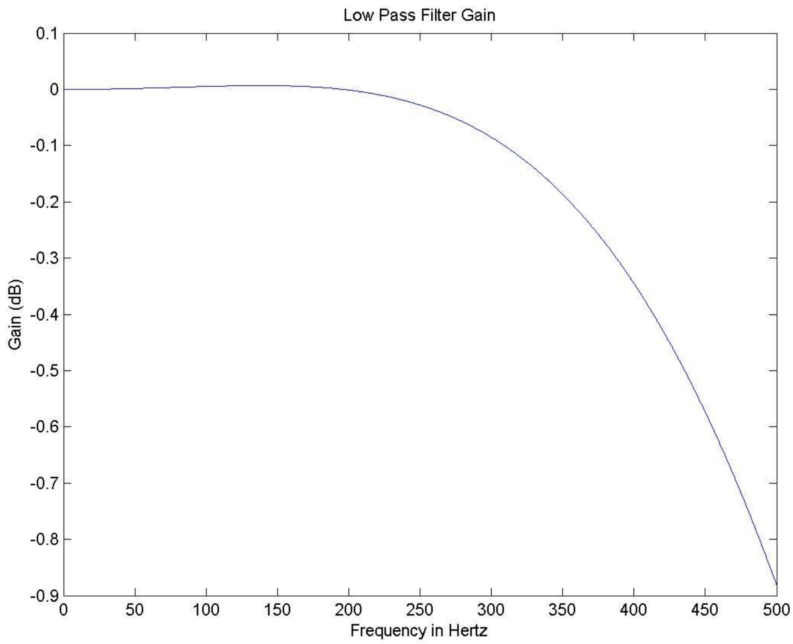

Figure 34: Magnitude Response of Low Pass Filter in dB

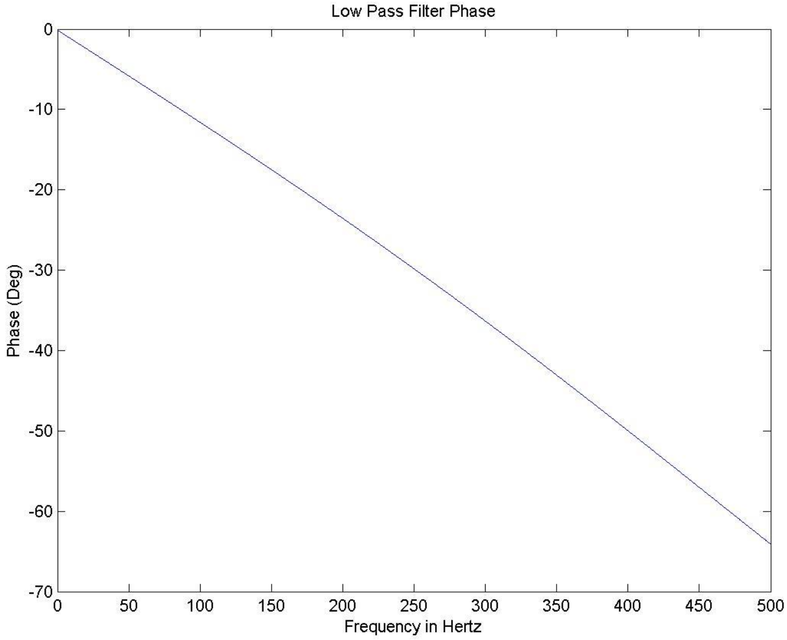

Figure 35: Phase Response of Low Pass Filter in Degrees

4.3 Digital Hardware

In order to process a raw signal with developed signal processing techniques, it should be discretized. In other words, the analog signal should be converted to a digital signal. Signal processing algorithms are complex and time consuming.Therefore, using a PC to perform signal processing is preferred. As a result,digital hardware is composed of two main parts; A/D converter and digital data transferringmicrocontroller.

Both of two main parts are realized using a microcontroller. The raw analog data is digitized by using internal A/D converter and sent to a PC. Transfer of digital data to PC may be done in any communication way that both microcontroller and PC support. Almost all of today's computers have Universal Serial Bus (USB) communication hardware due to its effectiveness at data transfer. Micro controller used in this study has also internal USB communication hardware and digital data is transferred to PC via USB.

PIC 18F4550 of Microchip Corp. is used as microcontroller in this study. PIC 18F4550 needs minimum number of auxiliary elements to operate and it has an internal A/D converter and an USB communication adapter. Since 8 A/D converters are needed in this study, the A/D converter in microcontroller is used in a time multiplexed methodology. Designed embedded software drives the A/D converter and digitizes the raw analog data. Then, buffered digital data belonging to independent channels are put into a message form. Finally, this message is sent to PC via formed USB communication channel.

Circuit schematics of digital hardware may be found at APPENDIX A. Data sheet of used microcontroller is also shared in [43].

4.4 Experiment Controller and EMG Interface Design

Monitoring of subsystems and raw EMG data is realized with main controller software. Raw EMG data recording is also done with this controller software. Main controller software acquires digital data sent by digital hardware and records raw EMG data. In addition to these, it processes raw signals and generates control commands. Then, these control commands are sent to robotic arm via another independent USB port. Therefore, hardware of robotic arm and EMG data acquisition system is fully isolated. They are integrated via main controller software. In this part, details of main controller software and its interface with other subsystems are explained.

Flow chart of main software is given in Figure 36.

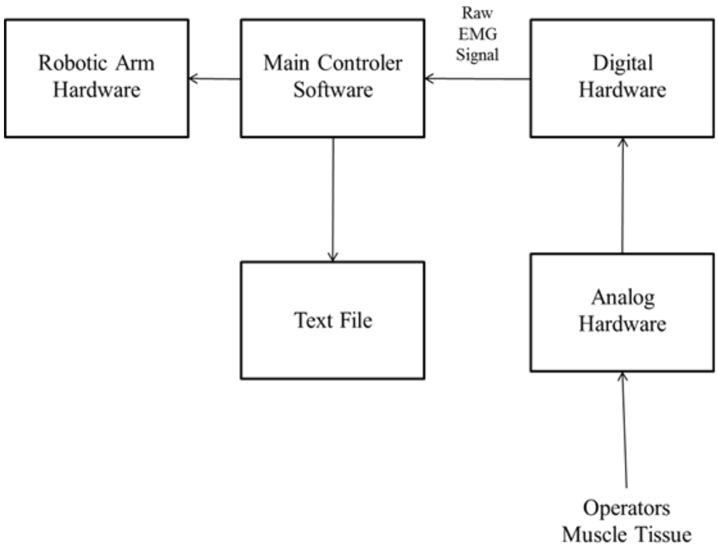

Figure 36: Flowchart of Main Controller Software

The main software is composed of three threads. User interface is controlled with an independent thread. As a result, user is capable of changing system state without any interruption. Data acquisition is realized with an independent thread, as well. Fresh raw data is recorded and transferred to signal processing thread. Lastly, signal processing thread processes raw EMG data and generates control commands for robotic arm. As final products, these control commands are sent to robotic arm controller. Since, main software is developed in a multi-thread architecture; it has small time delay during acquiring digital data, processing it, and sending commands to robotic arm. Three different threads are started in proper timing order and ended in accordance with state of the software. Main controller software is controlled with a user-friendly graphical user interface allowing the EMG operator to manage the EMG sessions easily.

Since this software runs under Windows operational software (OS) and Windows is not a real time OS, controller software may not be accepted as real time software.

Controller software is developed in Borland Developer Studio software development environment which provides a useful framework for computer applications based on object oriented programming (OOP).

CHAPTER 5

EXPERIMENTAL RESULTS

As stated in the previous chapters, algorithms on feature extraction stage and classification stage have important effect on the overall system performance. Several tests are carried out with these algorithms and performance results are obtained. These results and comparisons of these algorithms are presented in this chapter.

Firstly, results of time domain algorithms are shared. Effect of different time domain features on system accuracy is provided with results obtained from real test data.

Secondly, accuracy of frequency domain based algorithmsare shared. As a measure of their accuracy, recognition performance of the frequency domain features are used. Success rates ofrecognitions are directly related to distinctiveness of frequency domain features and they are good indicators about overall system performance.

Finally, accuracies of time domain and frequency domain feature based algorithms are compared. Different parameters which affect overall system performance are used in the evaluation of these algorithms.

5.1 Results of Time Domain Algorithms

As stated in Chapter 3, there are several time domain features that can be extracted from raw EMG data. In this part, these features are investigated in detail and accuracies of these algorithms are provided.

As mentioned in chapter 4, main controller software records raw EMG data for post processing purposes. One of these records is used as test data and presented results are obtained from this real EMG data. Results of different algorithms on this test data are provided.

Before sharing the test results of the time domain algorithms, success criteria should be well defined. The raw EMG data is shared with the time intervals that user desires to activate related servo motor. The time intervals, in which the operator is assumed that he is trying to activate a servo motor, are determined perceptually. Although perceptual determination method is erroneous, in proposed HMI system, this induced error has significantly small effect. In addition, time intervals, that time domain features exceed a certain threshold, are also given. As a result, success criteria applied to algorithms is that the amount of match of these time intervals. In other words, algorithms are evaluated according to how successful they distinguish whether operator desires to activate servo or not. Figure 37 shows the time intervals in which the operator desires to activate a servo motor.

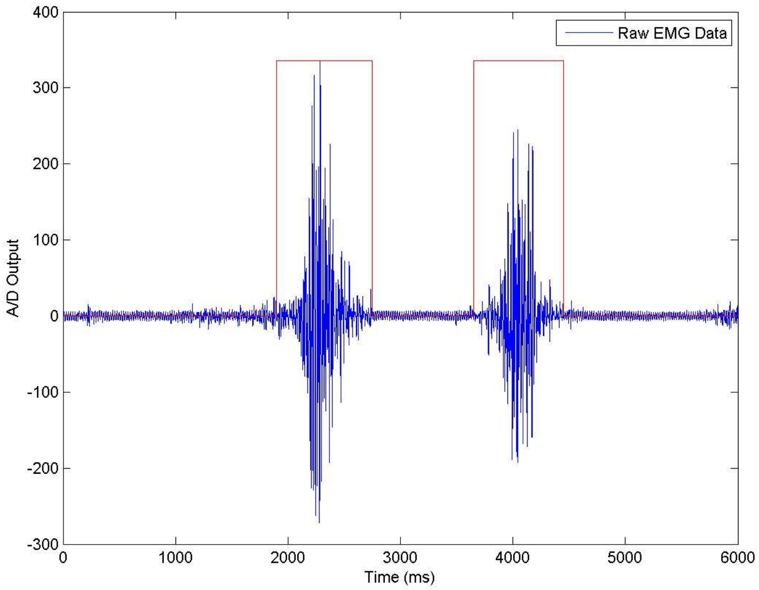

Figure 37: Raw EMG Data Used to Test Algorithms

Definition of Integrated EMG (IEMG) feature is shared in Chapter 3. Calculated IEMG from a sample test data is also shared in Chapter 3.

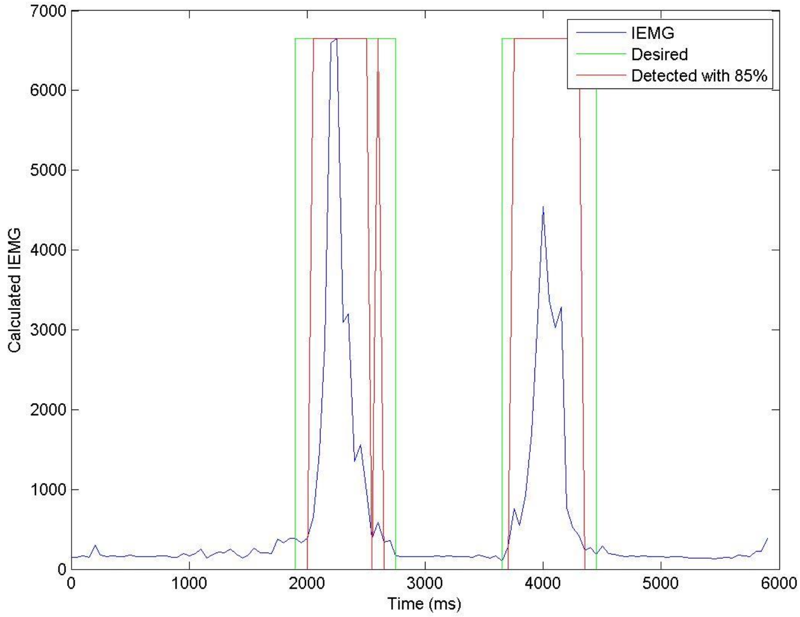

Figure 38: Calculated IEMG and IEMG Activated Time Intervals

As it is seen from Figure 38, IEMG activated time intervals 85% match with the time intervals in which operator desires to run the servo. Therefore, performance of IEMG feature is 85% with a suitable threshold. In other words, when IEMG feature extracted from raw EMG signal in order to form a one dimensional feature vector, comparing IEMG value with a pre-defined threshold has 85% success rate.

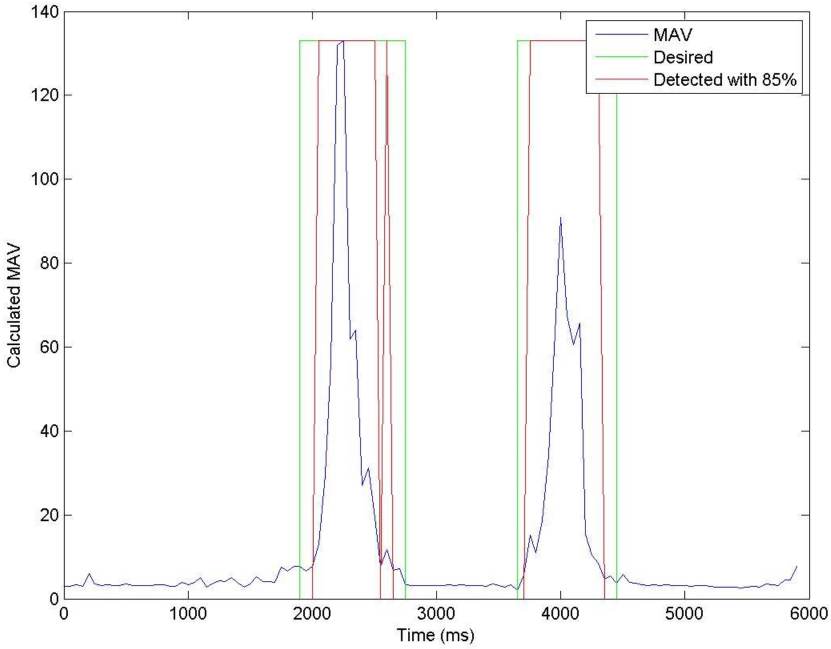

Figure 39: Calculated MAV and MAV Activated Time Intervals

When definitions of Mean Absolute Value (MAV) and IEMG given in chapter 3 are compared, they are separated only by a normalization factor. Therefore, MAV feature has also 85% success rate with a suitable threshold. In addition, since Mean Absolute Value Slope (MAVS) is simply time derivative of MAV, it has very close success rate with MAV.

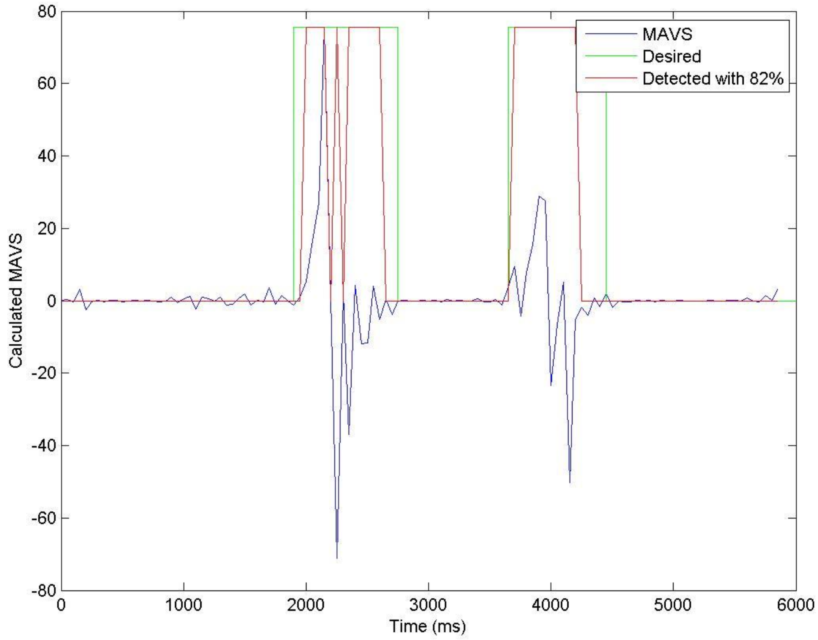

Figure 40: Calculated MAVS and MAVS Activated Time Intervals

Root Mean Square (RMS) feature calculated from raw EMG signal is also an important indicator whether operator wants to run related servo or not.

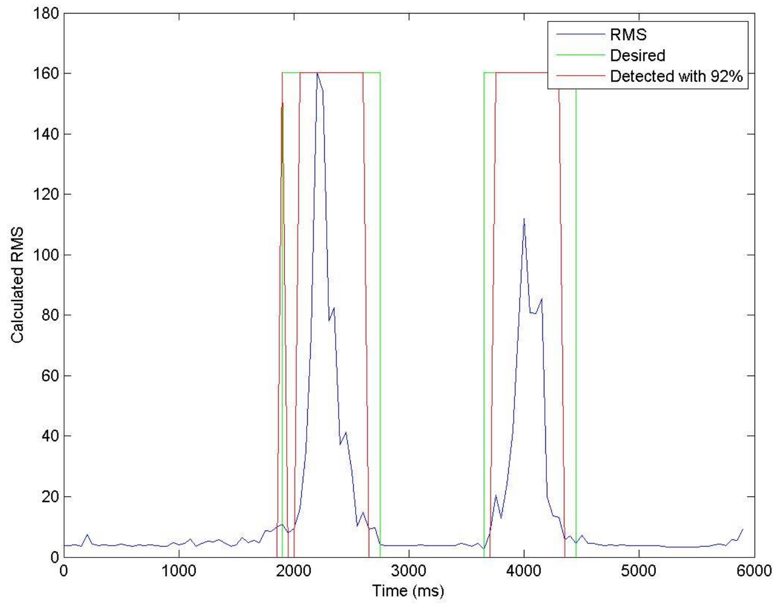

Figure 41: Calculated RMS and RMS Activated Time Intervals

As seen from Figure 41, RMS feature also activates servo with 92% accuracy. Simple Square integral (SSI) and Variance (VAR), which are closely related with RMS,activate servos on robotic arm with success rate of 88% and 85% respectively.

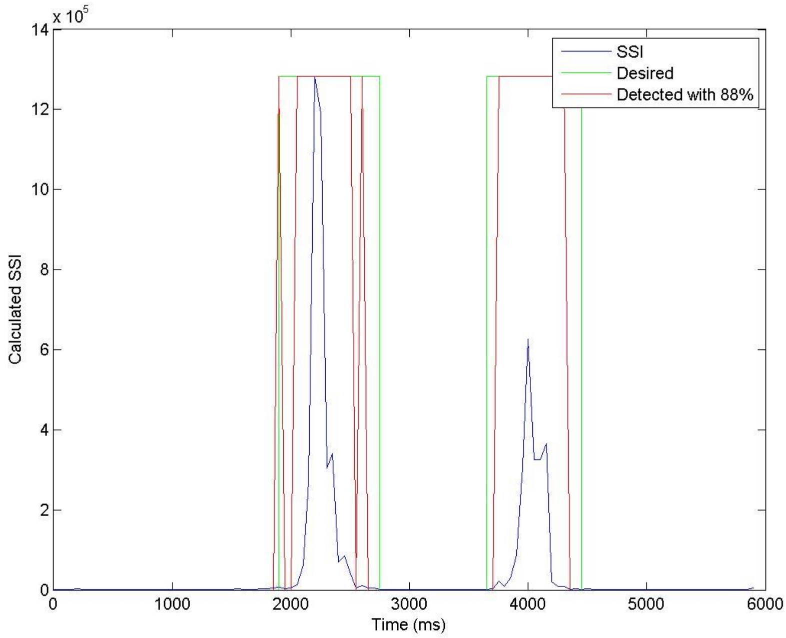

Figure 42: Calculated SSI and SSI Activated Time Intervals

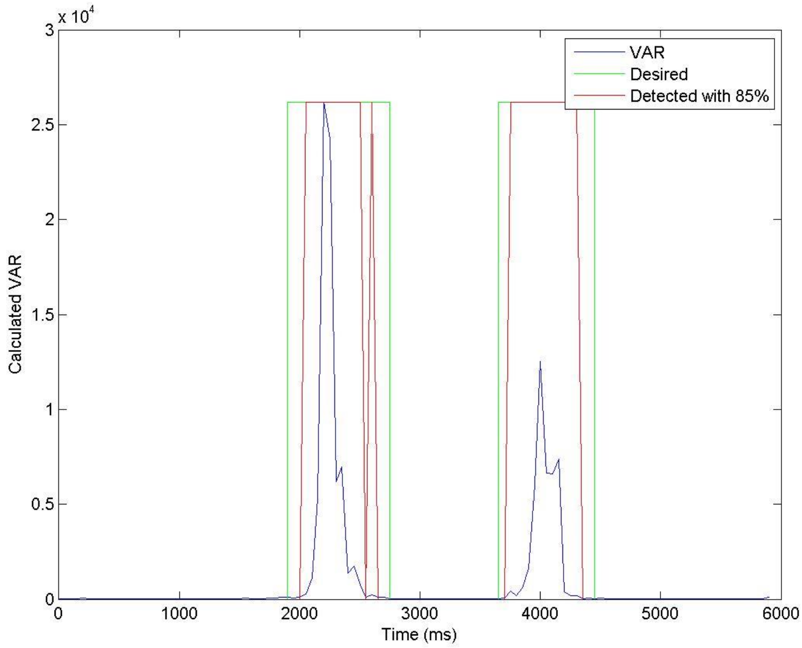

Figure 43: Calculated VAR and VAR Activated Time Intervals

Waveform Length (WL), Zero Crossing (ZC), Slope Sign Change (SSC), and Willison Amplitude (WA)are the time domain features which are closely related to frequency domain features. Actually, their amplitude is directly related to dominating frequency component of raw EMG signal. By applying a proper threshold, these features may easily trigger the related servo.Figure 44, Figure 45, and Figure 46provides activation time intervals of WL, ZC, SSC features. They have success rates of 92%, 97%, 85% respectively. WA has also a high success rate of 91%.

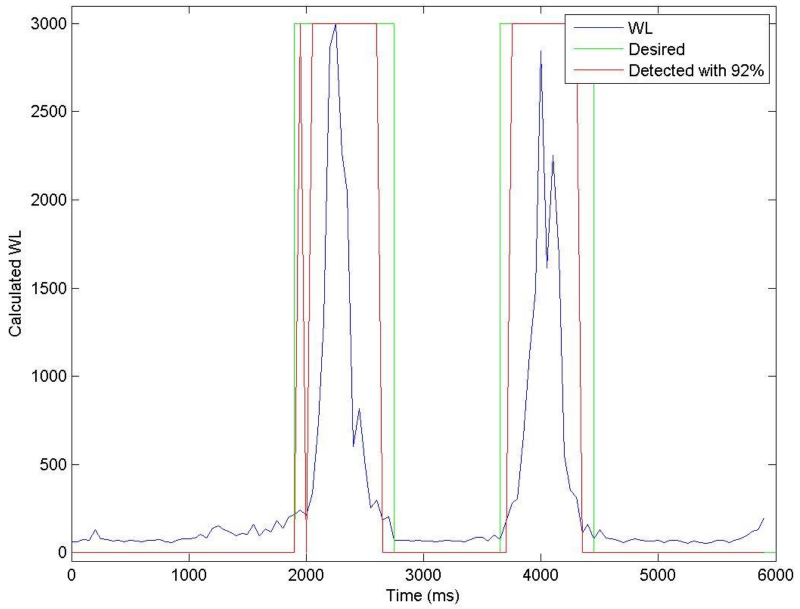

Figure 44: Calculated WL and WL Activated Time Intervals

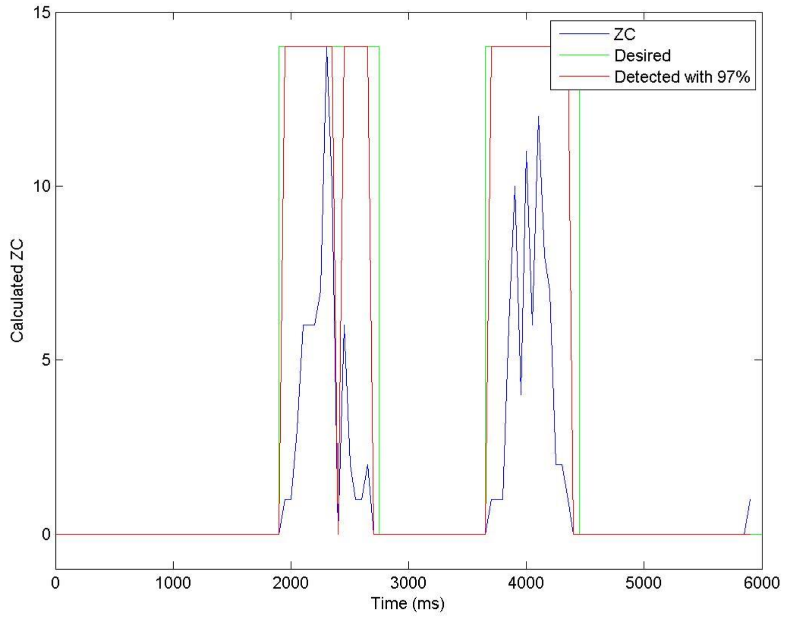

Figure 45: Calculated ZC and ZC Activated Time Intervals

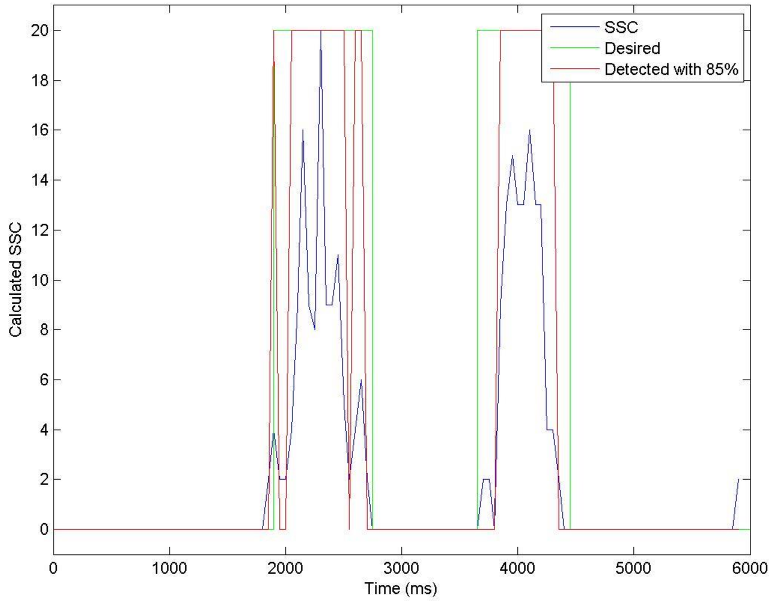

Figure 46: Calculated SSC and SSC Activated Time Intervals

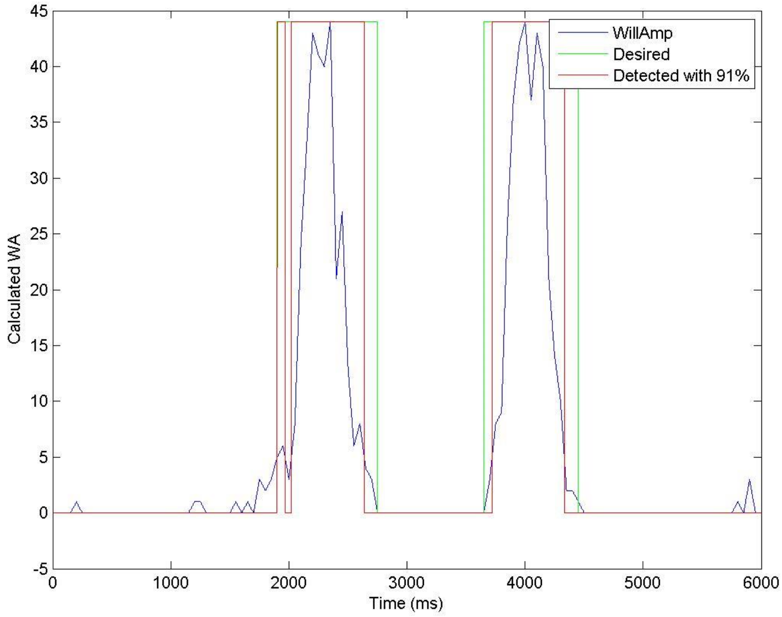

Figure 47: Calculated WA and WA Activated Time Intervals

As shown in Figure 38-Figure **47**, time domain features have very high success rates, and they are easy to implement. The most important point that should be identified in this study is that time domain features are not used to distinguish certain arm movements. They are used to sense contraction levels of muscle tissues. Corresponding servos on the robotic arm are driven in accordance with these contraction levels.Operators are educated about how to use this HMI system.By contracting certain muscles, corresponding servos on robotic arm are activated. As a result, time domain features are used to sensecontraction of muscle tissues with very high success rates.This is the main reason why time domain algorithms are implemented in nearly real time system.

5.2 Results of Frequency Domain Algorithms

As stated in Chapter 3, frequency median, frequency mean, and Auto-Regressive Parameters (AR Parameters) are used as frequency domain features and these featuresare not implemented in near-real time system. Frequency domain features are investigated by post-processing techniques.

Since frequency domain based algorithms are time consuming, and they are not implemented in the HMI system designed in this work, they are used to distinguish different arm movements. As a test scenario, electrical activity of biceps brachii is recorded for right arm while it is lifting two different weights, 4 Kg and 10 Kg.Recorded EMG data are post processedto extract some frequency domain features. These frequency domain features are used to distinguish these different arm movements. Therefore, the success criteriafor frequency domain algorithmsare the success rate of this recognition.

As it is mentioned in chapter 3, first AR parameter is used for recognition. These parameters are shared in Figure 48 and Figure 49.

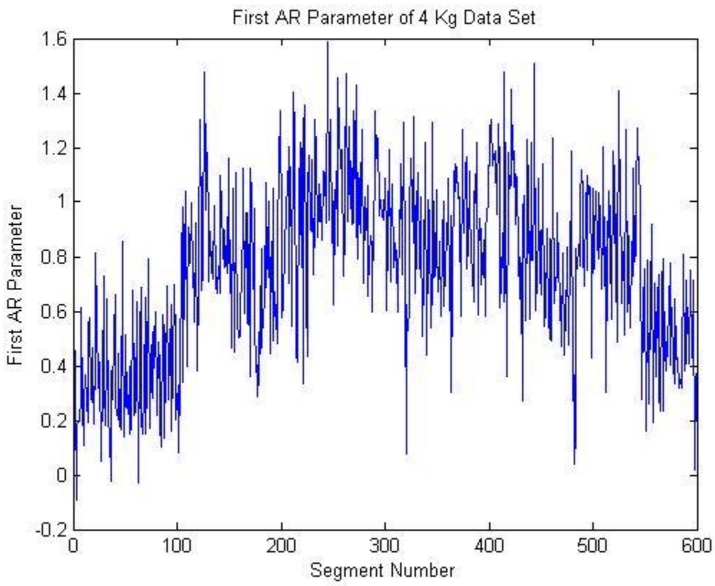

Figure 48: First AR Parameters of 4 Kg Data Set for Each Segment

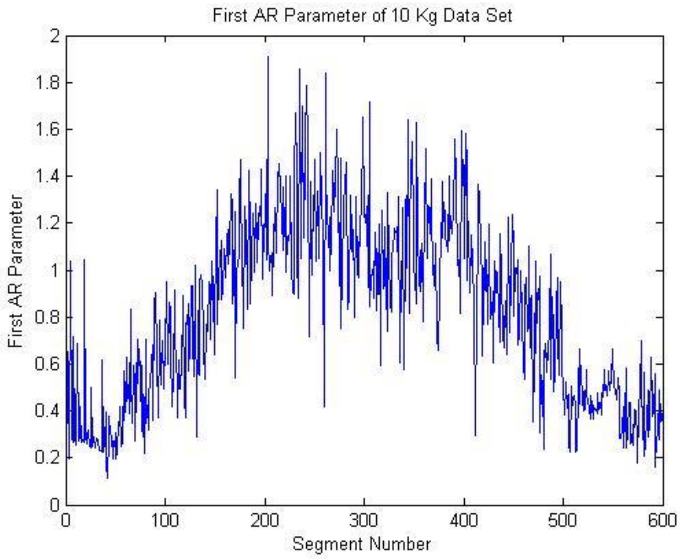

Figure 49: First AR Parameters of 10 Kg Data Set for Each Segment

It is observed that these AR parameters are distinctive enough for recognition. 40 repetitions of same movement is realized and recorded for both 4 Kg and 10 Kg lifting. During application of SVM algorithm, 50% of data log is used for training and rest is classified. This test is repeated for 1000 times and mean of error rate of recognition is 28.53%, with standard deviation of 1.12%.

Additional frequency domain features;such as frequency mean and frequency median; are also described in Chapter 3. These features are also extracted from the raw EMG data which aregiven in Figure 37.As mentioned in Chapter 3, frequency domain features are calculated by using power spectral density.On the other hand, modified frequencydomain features are calculated from the amplitude spectrum. Therefore, they are closely related and their performances are very close.

Frequency mean and median features are extracted with post processing and they are used to distinguish different arm movements. In these tests, 4 Kg and 10 Kg lifting EMG records are used. Similar to AR parameters, 50% of test data is used for training.

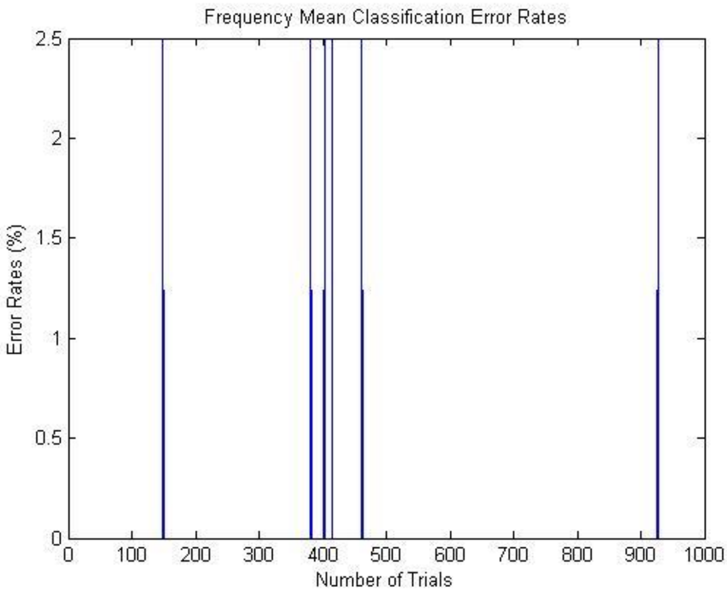

Figure 50: Frequency Mean Recognition Error Rates

Error rates for 1000 trials of recognition tests, which are realized with frequency mean feature, are shared in Figure 50. Frequency mean is very distinctive feature, therefore recognition error rates has a mean of 0.02% with standard deviation of 0.002%. Frequency mean parameters which are used in these tests are shared in Figure 51 and Figure 52.

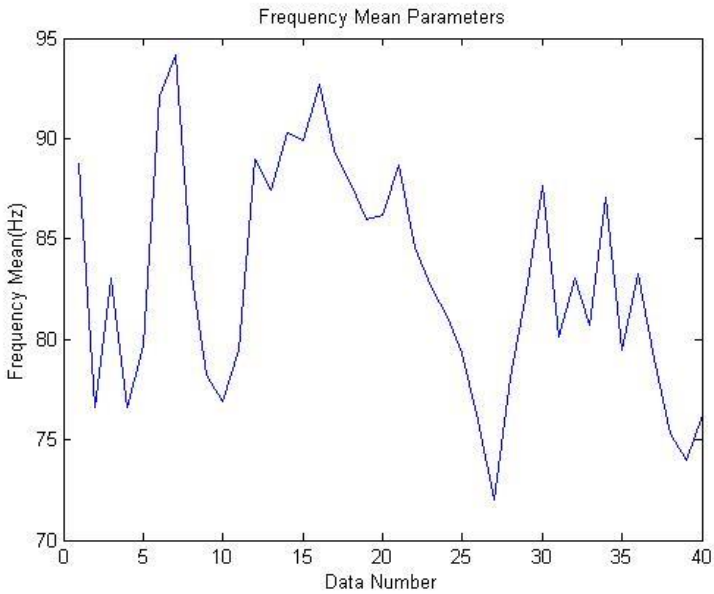

Figure 51: Frequency Mean Features of 4 Kg Data Set

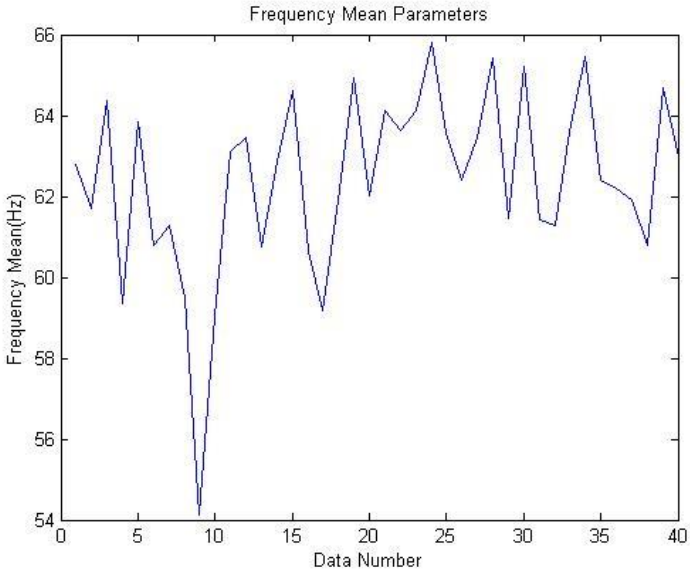

Figure 52: Frequency Mean Features of 10 Kg Data Set

As mentioned before, modified frequency mean feature is as distinctive as frequency mean feature.

When Figure 51andFigure **52** are compared, it may be observed that frequency mean feature of 10 Kg data set is smaller than 4 Kg data set. Power of EMG data at 4 Kg data set is less than EMG data at 10 Kg data set. Therefore, frequency mean of 4 Kg data is more close to frequency mean feature which is calculated when muscle is in idle state. This result is shared in Chapter 3, as well. On the other hand, EMG data at 10 Kg set is more powerful when compared to 4 Kg set. Therefore, its frequency mean is more close to natural EMG mean frequency.

As frequency median feature is fed to the SVM algorithm, success rate of recognition significantly decreases. Frequency median feature has 53% success rate at 1000 trials. Therefore, frequency median should not be used in gesture detection. By definition, frequency median is the frequency which splits power spectral density into two equally powered parts. Since spectrum of background noise and raw EMG signal overlaps, frequency mean feature does not change significantly from gesture to gesture. Modified frequency median is very closely related with frequency median feature. As a result, it has also very low success rates at recognition.

5.3 Comparison of Time and Frequency Domain Algorithms

As it is understood from previous parts, time domain features and frequency domain features are not used with the same objective. Therefore, their comparison,based on their performances in this study, may only be used to identify their advantages and drawbacks.

Time domain features are extracted with fast algorithms and they are more distinctive. In addition, some of the time domain features have indicative information about frequency domain features. Therefore, time domain features can also be used for a movement recognition purpose. The reason of why time domain features are not used for movement recognition in this study is that success rate of recognition with time domain features decreases as movement variety increases. In this HMI application, lower recognition success rates may cause overall system to be useless. Therefore, in this study, time domain features are used to sense contraction levels of muscle tissues with high success rates. However, most important drawback of time domain features is that they are very sensitive to background and instrumentation noise. Therefore, data acquisition system performance has a direct effect on time domain algorithms.

Although frequency domain features are extracted with time consuming algorithms, they are distinctive in movement recognition applications. In addition, frequency domain based algorithms are more robust to background and instrumentation noise. Therefore, these algorithms decrease effect of data acquisition system on overall system performance. When results of frequency domain features are investigated, it is observed that high gesture detection rates are obtained. However, these rates are obtained with post processing. Extraction of frequency domain features in real-time flowing data is more complex and time consuming. This effort may be accepted in cases that number of independent data sources is limited and number of classes is high.

As a result, there is a tradeoff between computation complexity and number individual classes and independent data channels. The designer should carefully decide feature type and number of channels.

CHAPTER 6

CONCLUSION

In this thesis, an implementation of EMG driven HMI system is performed. Data acquisition unit and algorithms are designed in scope of this study.Proposed HMI system aims to drive the robotic arm by using EMG signals obtained from the operator. Several performance tests are realized and reliable system performance is obtained. Designed HMI system is able to drive the robotic arm with a specific purpose.General view of the robotic arm which is used in this study is shown inFigure 53.

Figure 53: The Robotic Arm AL5D

Both time domain and frequency domain features are examined. There are two different work completed with feature extraction studies. First a near-real time HMI system is designed by using contraction state of specific muscle tissue.Then, performances of features on gesture detection are evaluated. Results of these works are shared inTable 4.

Table 4: Results of Time/Frequency Domain Feature Extraction Algorithms

Time/Frequency Domain Feature	Success Rate
Integrated EMG	85%
Mean Absolute Value	85%
Mean Absolute Value Slope	82%
Root-Mean-Square	92%
Simple Square Integral	88%
Variance	85%
Waveform Length	92%
Zero-Count	97%
Slope Sign Change	85%
Willison Amplitude	91%
Auto-Regressive Modeling	72%
Frequency Mean	99.98%
Frequency Median	53%

6.1 General Observations and Discussions

Several design criteria are satisfied and tests are performed. Some observations are made after overall system design and tests are completed.

First observation is that the relation between independent data channels and number of individual classes should be well managed. As the number of independent data channels decreases and more classes are desired to be identified, the only way is to detect gestures of operator. In addition, correlation between “independent” EMG data for different gestures increases. Therefore, extracted features lose their indicative properties. In cases where class number is high, contraction state driving methods which are implemented in this study may be used. It should not be forgotten that contraction state driving methods requires more data channels.

Second, the designer should be aware of the fact that EMG signal is not stationary. Therefore, while extracting frequency features from raw data, segmentation length should be chosen carefully. Especially, in AR parameter calculation, as described in chapter 3, residuals are good indicators of estimation success. These residuals are expected to be white noise. It is important to improve modeling quality to have a better recognition performance.

Third, the whole system should be tested with more people from different age groups, and gender. Proposed HMI system is tested with only two people and some additional tests are required to be performed.

Lastly, hardware and software design are also important for overall system performance. The most important parameter which effects user satisfaction is that time delay between user's acts and movements of robotic arm. In the proposed HMI system, main control software runs on non-real-time operational software. Therefore, there is a delay of 300~500 ms during normal operational conditions. Software embedded in digital hardware is designed to minimize time elapsed from A/D conversion to complete transfer of digital data to PC.

6.2 Future Work

The thesis can be further improved with future studies on the following topics:

- Designed signal processing, recognition, and control command generating algorithms are implemented by asoftware which runs on Windows. A main board should be designed for this HMI application.Designed algorithms would run on this main board. Therefore, delay between muscle contractions and robotic arm movements may be shortened.In addition, computational time may be shortened significantly.

- The developed near-real time HMI system is only applicable for time domain features. Frequency domain signal processing algorithms are implemented in post-processing analysis environment. In this study, success rates in offline recognition experiments are used as performance criteria. These frequency domain algorithms should be implemented in a real time HMI system.

- The HMI system implemented in this thesis drives only a robotic arm. As mentioned in chapter 2, it is also possible to control different devices by using EMG signal. Some different devices, which need less distinct classes for driving purposes, may be controlled with the proposed HMI system. Designed hardware may also be updated accordingly, as well.

- Another point in this study which should be improved is the designed analog and digital hardware. All printed circuit boards are produced by hand and circuit elements are soldered by hand. A better performance may be achieved by developed production techniques. Dimensions of circuits may be reduced by using small elements, as well.

- In this study, it is shown that the information extracted from raw EMG signal may be used for HMI applications. In future studies, some torque and force estimation algorithms may be studied in order to drive some paralyzed muscle tissues for functional purposes. As it is mentioned before, during the evaluation of time domain features, start of muscle contraction is determined perceptually. Some mechanical force measurement instrumentation may be introduced as a ground truth to determine muscle contractions.

Figure 54: An Operator Running Proposed HMI System

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APPENDIX A

EMG HARDWARE SCHEMATICS

The circuit diagram of the designed high-pass and low-pass circuitsare shown in Figure 55 and Figure 56. Cut-off frequencies are 3 Hz for high-pass filter and 500 Hz for low-pass filter.

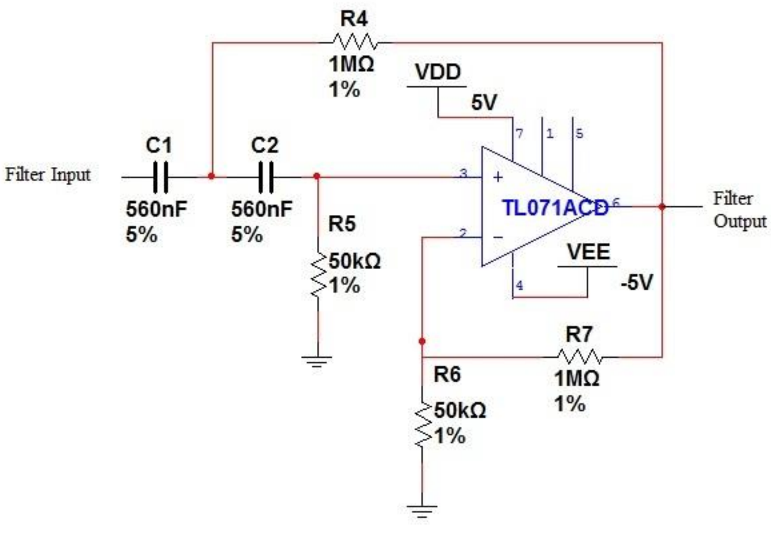

Figure 55: Second Order Butterworth High Pass Filter

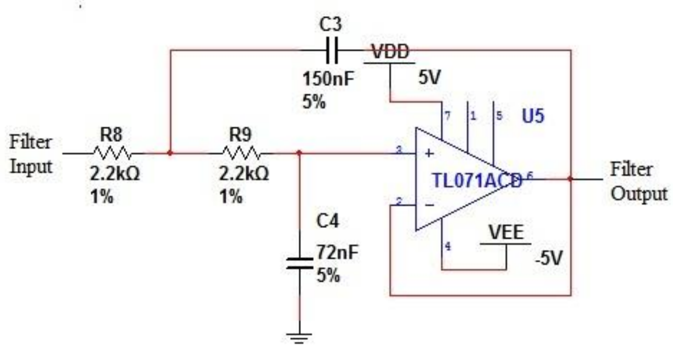

Figure 56: Second Order Butterworth Low-Pass Filter

These active filters are cascaded in order to have band-pass filter. High-pass filter has a pass band gain of 25. On the other hand, low-pass filter has unity pass band gain. Overall analog circuit including pre-amplification stage is shown in Figure 57. Circuit in Figure 57is implemented for each individual channel.

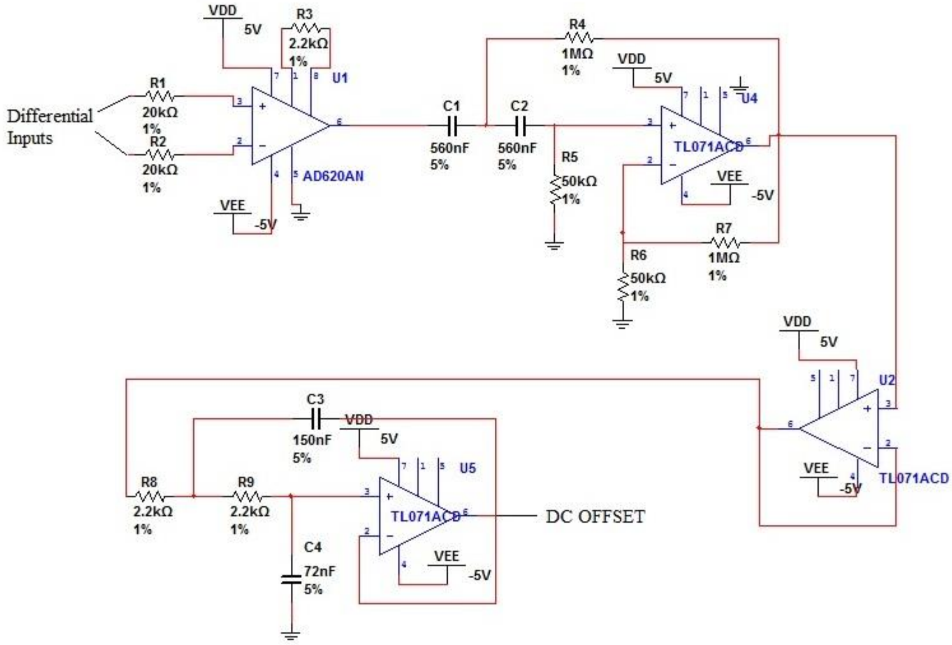

Figure 57: Overall Analog Amplification Circuit for Each Channel

EMG signal is naturally a zero-mean signal.Therefore, before A/D conversion, a DC offset is required to be added to amplified raw EMG signal. Summing amplifier shown in Figure 58is used for DC offset addition.

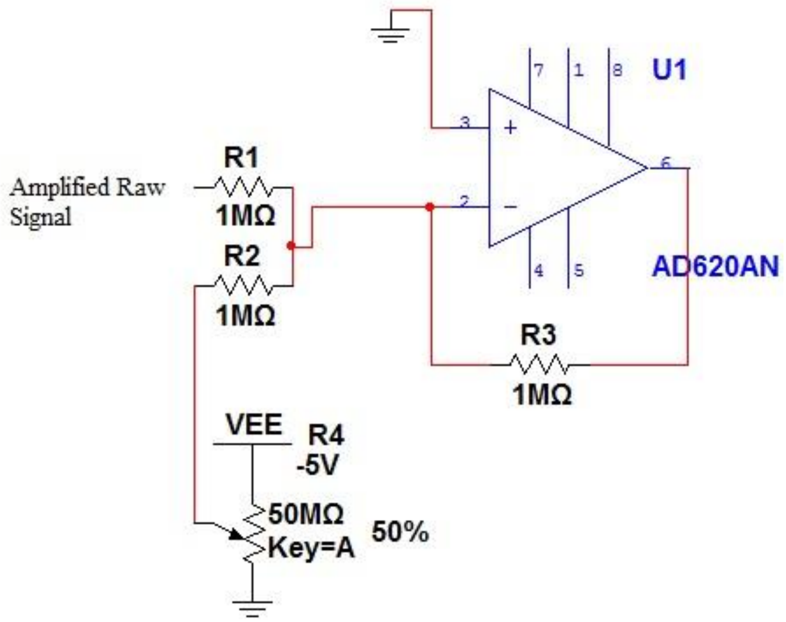

Figure 58: Summing Amplifier for DC Offset Addition

Schematic of digital hardware is provided in Figure 59.

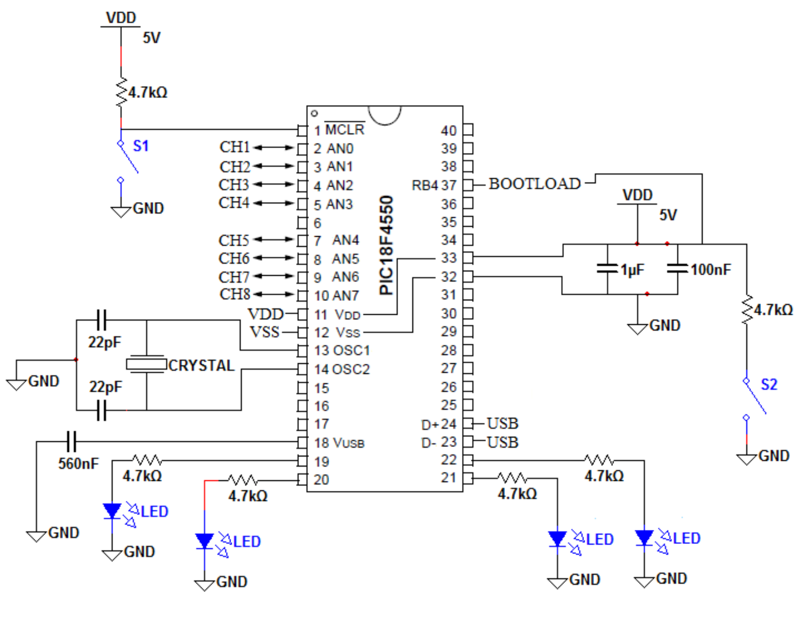

Figure 59: Schematic of The Digital Circuit

Common Mode Rejection Ratio of analog amplifier circuit with respect to frequency is provided in Figure 60.

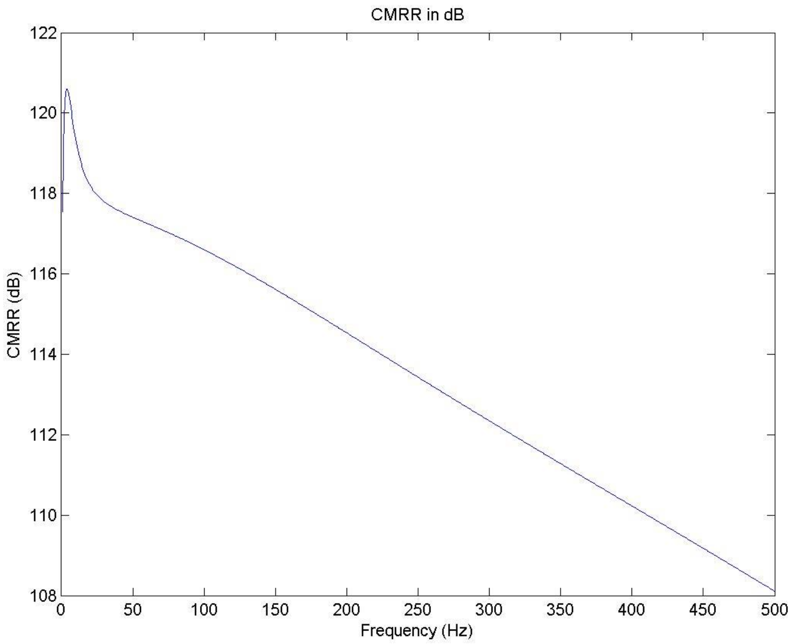

Figure 60: CMRR of Designed EMG Amplifier vs Frequency