DESIGN AND DEVELOPMENT OF PROSTHETIC ARM FOR ABOVE-ELBOW AMPUTEES

Thesis

Submitted for the award of

DOCTOR OF PHILOSOPHY

by

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Dedicated to

my parents Sh. Harbans Lal,
Smt. Nirmala Devi,

for giving me the

Precious gift of education

and to

my son Suryaakirti Rudraa

who added all the colors to my life

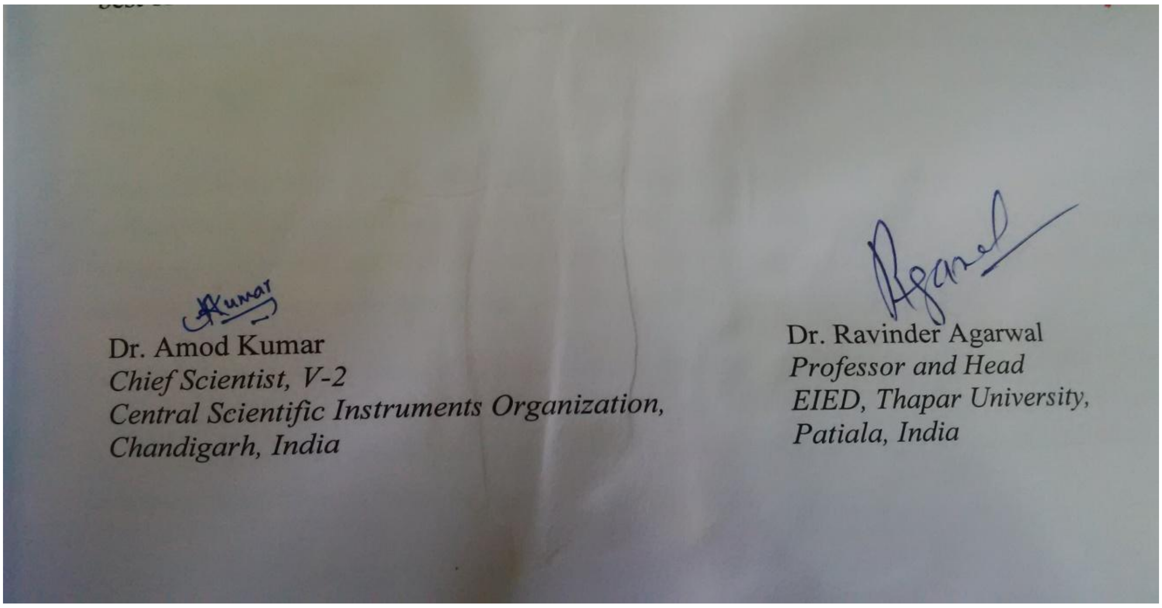
CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "**Design and Development of Prosthetic Arm for Above-Elbow Amputees**", for the award of degree of **Doctor of Philosophy** in Electrical and Instrumentation Engineering Department (EIED), Thapar University, Patiala, is an authentic record of my own work carried out under the supervision and guidance of Dr. Ravinder Agarwal, Professor, EIED, Thapar University, Patiala and Dr. Amod Kumar, Chief Scientist, Central Scientific Instruments Organisation (CSIO), Chandigarh.

The results presented in this thesis have not been submitted in part or in full to any other University or Institute for the award of any degree or diploma.

(KARAN VEER)

This is to certify that the above statement made by the candidate is correct and true to the best of our knowledge and the contents of the thesis have reached the requisite standard.



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ABSTRACT

People's working capability is badly affected when they suffer with an amputated arm. Artificial replacements with prosthetic devices to get a satisfactory level of performance for essential functions with the currently available prosthetic technology are very difficult. Myoelectric arm prostheses are becoming popular because they are operated by natural operations of intact muscles. The objective of this work is to explore the various methodologies and algorithms used for surface electromyogram signal classification for the purpose of implementing the same in the developed prosthetic hand.

In the present work, surface electromyogram (SEMG) acquisition system was designed keeping the economics and application in mind. After acquiring the signal, important aspect is to extract the features which are representative of surface electromyogram pattern for different arm functions. The study of different parameters in relation to signal variations with force level was carried out and it was found that both amplitude-related parameters and selected statistical parameters give good indication of force level. Further, the electrode placement points were compared with other locations on arm for best surface electromyogram acquisition. Interpretation of surface electromyogram signals using advanced techniques is a very important requirement in biomedical engineering. Recent advances in technologies of signal processing and mathematical models have made it possible to achieve this objective. Further electromyogram has encouraged human computer interactions for developing myoelectric signal based prosthetic devices.

In the present research work, the main emphasis is on the study of surface electromyogram (SEMG) signals at multiple muscles points with different postures or movements for designing prosthetic device having usable degrees of freedoms (dof). Further, development and testing of the designed prosthetic arm on different amputees has been carried out.

The objectives of this research include:

1) To develop electrode system for acquiring SEMG data from above-elbow amputees.
2) To simulate and analyze stored SEMG for different postures from three classes of above-elbow amputees.
3) To compare the actual SEMG with simulated model and verify the results with the help of soft computing techniques.
4) To design and develop electronic circuitry / mechanical structure for development of prototype model of 4 Dof prosthetic arm.

Objective 1: Surface electromyogram is a complex signal, which is controlled by the nervous system and is dependent on the anatomical and physiological properties of muscles. Surface

electromyogram detector (electrode) at the surface of the skin collects signals from different motor units at a time, which may generate interaction of different signals. These signals get corrupted by noise while traveling through different tissues. The sources of these noises are environmental (such as 50 Hz power-line) or biological (such as motion artifact) interference. Due to these complexities, detection of surface electromyogram signals with powerful and advance techniques is becoming a very important requirement in biomedical engineering.

In order to utilize surface electromyogram as input to control assistive devices or prosthesis, the essential step is the processing of the signal to extract features from it, and classify the signal for different types of desired motions. Interpretation of surface electromyogram signals using advanced techniques is equally important. Recent advances in technologies of signal processing and mathematical models have made it possible to achieve this objective and have encouraged human computer interactions for developing myoelectric signal based prosthetic devices. The surface electromyogram acquisition system was developed to measure and record the signals from the subjects. Users have the options to select a variety of voltage scales and time scales to display the output signals with great advantage of portability.

The very first stage in the signal processing is pre-amplifier stage. A differential amplifier has been used as a preamplifier, which amplified the signal by a gain of 5 with Common Mode Rejection Ratio (CMRR) greater than 90 db. The signal was again amplified by a non inverting amplifier in second stage with a gain of 1000. The purpose of the non-inverting amplifier was to provide fine tuning of the gain needed. In order to extract spectral components that contain important information, electrodes placement as far as possible from each other in transverse direction is necessary. The inter-electrode distance was kept as 1 cm. Three electrodes were used for the signal acquisition. The sampling frequency used for the acquisition was 1000 Hz. In the next stage, interfacing was done to connect the surface electromyogram signal amplifier circuit to the computer through data acquisition card (DAQ).

Objective 2: In this investigation, the study of surface electromyogram (SEMG) signals at different above-elbow muscles for different operations of the arm like elbow flexion/extension, abduction/adduction was carried out. The whole system consists of surface electrodes, signal acquisition protocols and signal conditioning at different levels. A program code was written and used for acquiring the surface electromyogram signal from the designed hardware. Many amputees having active residual stump participated as subject in this reported work. The surface electromyogram signals were recorded from their residual muscles and relevant features were extracted for representing the surface electromyogram patterns against different arm functions.

Objective 3: the study of different parameters in relation to surface electromyogram variations with force level has been carried out and it has been found that both amplitude-related parameters and selected statistical parameters give satisfactory estimate of force level. It has also been observed that prolonged use of the prosthetic device may result in lower amplitudes of surface electromyogram signals. Thus, a prosthetic controller based on amplitude should have the capability of adjusting the threshold level in order to get proper degree of controllability.

A number of amplitude based parameters were tried which reflected good representation of the surface electromyogram. The Fourier transform, power spectral density estimation and the statistical parameters have been discussed. These parameters have been experimented with variable force exerted by the muscles of above-elbow. The interpretation of surface electromyogram from multiple locations on arm for four independent movements of arm was carried out. To know the effectiveness of quality of recorded surface electromyogram Principal Component Analysis (PCA) and repeated factorial Analysis of Variance (ANOVA) techniques were implemented.

The surface electromyogram amplitude variations resulted into linearity of the maximum voluntary contraction of a subject until fatigue occurs. The study of different functions of arm along with the movements required to perform those functions has led to a practical solution. The functional jobs of human hand can be divided into two major categories, i.e. based on day to day work and skilled work. It is quite evident that 90% of day-to-day functions are grasping and release movements. These works normally require one out of four movements like elbow extension, elbow flexion, abduction and adduction. Reporting has been done about the methods of processing and analyzing surface electromyogram signal for upper arm motions for extracting accurate patterns of the signal. From these recorded signals, amplitude features were extracted. Then a comparative study to evaluate the wavelet denoising for optimal motor unit action potential detection through the decomposition based on the different wavelet functions of Daubechies, Coiflet and Symmlets families was made and tabulated. Linear Discriminating Analysis and Artificial Neural Network pattern classifier approaches were employed to analyze classification performance for different upper arm movements for the effectiveness of recorded surface electromyogram signals for class separability of upper arm motions.

Objective 4: Finally, the developed surface electromyogram signal based prosthetic device is presented. The electronic design consisted of analog and digital signal processing and controlling circuit and mechanical assembly consisted of wrist, palm and the fingers to grip the object in addition to a screw arrangement connected to a low power D.C. motor and gear assembly to open or close the hand. The wrist is mechanically rotated to orient the hand in a direction suitable to pick up/hold the object. The entire set up is placed in a casing which provides a cosmetic appeal to the artificial hand and the connected arm. The design criteria include electronic control, reliability, light weight, variable grip force with ease of attachment for simple operations like opening, grasping and lifting objects of different weight with grip force slightly more than enough just like that of a natural hand.

The design employs a converter with Gain amplifier, which is used to convert the RMS amplitude value into proportional dc value so that signal strength can be averaged. The output level of converter is low in relaxed state of hand while it increases due to muscle contraction as hand opens. A variable DC gain amplifier is used in order to bring uniformity in DC signal level. An 8-bit Analog to Digital converter is used to digitize DC signal output which is fed to microcontroller to control relays used to achieve variable grip force. The design imposes limits on the "OPEN" and "CLOSE" movement of hand through optical switches which provide signals to microcontroller so as to stop motor at finger extremities and change of direction takes place subsequently.

CONTENTS

ACRONYMS

ADS	=	Arm Disabled Subject
AE	=	Above Elbow
ANOVA	=	Analysis of variance
ANN	=	Artificial Neural Network
BE	=	Below Elbow
BMI	=	Body Mass Index
CMRR	=	Common Mode Rejection Ratio
DAQ	=	Data Acquisition Card
DOF	=	Degree of Freedom
DWT	=	Discrete Wavelet Transform
ECG	=	Electrocardiogram
ED	=	Euclidean Distance
EE	=	Elbow Extension
EEG	=	Electroencephalogram
EF	=	Elbow Flexion
F_C	=	Critical value
LDA	=	Linear Discriminant Analysis
ME	=	Myoelectric Signals
MDF	=	Median Frequency
MNF	=	Mean frequency
MMI	=	Man Machine Interface
MS	=	Mean Square
MUAP	=	Motor Unit Action Potential
NCS	=	Nerve Conduction Study
NMJ	=	Neuromuscular Junction
PCA	=	Principal Component Analysis
RMS	=	Root Mean Square
SEMG	=	Surface Electromyogram
SSB	=	Sum of Square Between
SSW	=	Sum of Square Within
UE	=	Upper Extremity

1

INTRODUCTION

According to a survey conducted in 2007, there were approximately 1.7 million people living with limb loss in the United States. It is estimated that one out of every 200 people had an amputation. Worldwide, number of amputees is approximately four millions and there is an increase of 150,000 to 200,000 people every year. Upper-limb amputations account for about 68% amputees. Out of this, old amputees are about 30 %, 60 % are between 21 to 60 years old and remaining 10 % are under the age of 21 years. It is estimated that the number of amputees with no prosthesis increases annually by about 17,000. It can be further correlated that the risk of traumatic amputations increases steadily with age, reaching its highest level among people of age 85 or older for both males and females. Males were at higher risk for trauma related amputation compared to females.

According to another statistics, out of the total limb amputees in USA, 30% have upper-limb amputation. Of this, 70% have amputations distal to the elbow. Figure 1.1 depicts the levels of an upper extremity amputation. Trauma is the most common reason for amputation in patients aged 15-45 years, with tumors being a distant second. Upper extremity amputations tend to be rare in patients who are older than 60 years, but they may be required secondary to tumor or medical disease [*Meier et al., 2005*].

According the International Federation of Societies for Surgery of the Hand, there are seven groups of malformations [*Ferguson et al., 2002*] [*Galiano et al., 2007*]:

- ❖ Failure of formation of parts
- ❖ Failure of differentiation (separation) of parts
- ❖ Duplication
- ❖ Overgrowth
- ❖ Undergrowth
- ❖ Congenital constriction band syndrome
- ❖ Generalized skeletal abnormalities

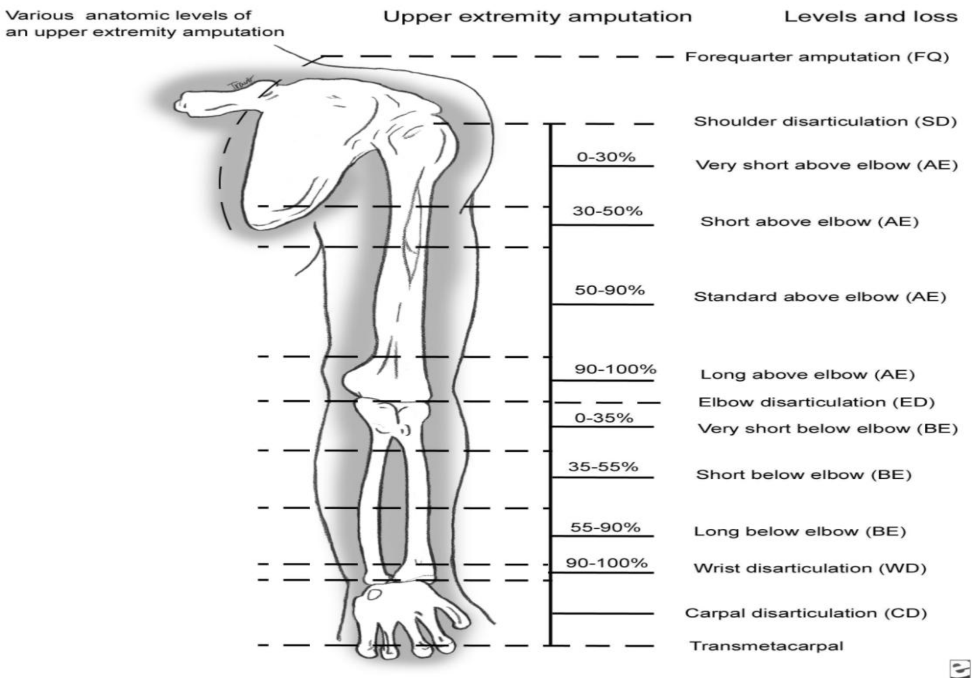


Fig. 1.1 Amputation levels [Ryait, 2011]

Malformations of the first group result in congenital amputations, the hand and the forearm being the most frequently affected. With the level of malformation, they are denominated as:

- Amelia: total absence of upper limb
- Hemimelia: absence of forearm and hand
- Acheiria: absence of hand
- Adactilia: absence of metacarpus and phalanges
- Aphalangia: absence of all phalanges

Surveys on using such artificial hands revealed that 30 to 50% of the handicapped persons do not use their prosthetic hand regularly because of low functionality, heavy weight and robot like movement factors [*Schulz et al., 2001*] [*Khezri et al., 2007*]. To overcome these disadvantages, lots of efforts have been made worldwide [*Online 1*]. Research activities have improved the functional range of an electrically driven prosthetic arm. As a result, actuators and mechanical elements have been used and the mass of the prosthetic device is reduced [*Online 2*] [*Merletti et al., 1999*].

1.1 PROSTHETIC ARM HISTORY

The history of prosthetics and amputation surgery began at the dawn of human medical thought. The word amputation is derived from the Latin word 'amputee' which means "to cut away" [*Kyberd, 1998*]. Over the centuries, the pace of development has been limited not only by technological progress but also by the small number of people surviving the trauma of amputation and the subsequent risk of infection. Prostheses were developed for function, cosmetic appearance and to provide a psychological sense. The prosthesis of ancient cultures began as simple crutches or wooden and leather cups as depicted in some of the earliest recovered pottery.

One of the earliest description of prostheses is by Herodotus in 484 BC which was made up of copper and wood. Leaving behind the historical gap, limb prostheses during 15th and 16th century was made up of iron and was designed by Ambroise Pare in 1536 for soldiers. Researchers developed arm prostheses in 1812 in which movement of arm and hand was controlled by using straps connected to opposite shoulder, but major interest in use of prostheses came after American civil war. Many of the prostheses developed during the 1900's were merely refinements of earlier armor type devices. They were bulky and heavy, but gradually gained more functional features [*Online 3*]. For many years, the standard means of control of the action of prosthesis has been through gross body motions of the amputee.

In the seventies, upper-limb prosthetic development of externally powered elbow and hand picked up the attention of researchers. The real value of externally powered components was not clear. The main purpose of study at that time was to determine whether externally powered components offer a significant contribution to the needs of the upper-limb amputee or whether they represent novelties which duplicate the functions of conventional mechanical components [*Tomovic et al., 1962*] [*Jerard et al., 1974*] [*Graupe et al., 1978*] [*Saridis, 1982*]. Based on these efforts, upper limb prosthetic devices came to be known as either passive or active. Passive prostheses are used for cosmetic purposes, with no moving parts whereas active prostheses may be body-powered or externally powered. Hybrids of these two systems also became available.

In the 1940's, the late Norbert Wiener observed that the biological signals that controlled actions which had been lost due to amputation, were still present in the body of the amputee. Professor Wiener suggested that few of these signals could be used to control prosthesis, instead of using gross body motions. The main advantage of such an approach is that its mode of control would be similar to the control of the corresponding body section that had been amputated. Thus one could logically expect that the amputee's ability to control the device would exceed his ability to control a conventional prosthesis [*Alter, 1966*].

The myoelectric prosthesis was implemented in 1945 by Reinhold Reiter. This type of prosthesis used sensors to detect a threshold of electromyography activity to switch an electric motor in the artificial ‘hand’ and could be used to switch powered wrist and elbow components [*Muzumdar, 1996*]. The electrically powered prosthesis under the control of myoelectric signals from residual muscles did not become commercially available until late 1960s and did not gain wide spread clinical acceptance until the early 1980s. Myoelectrically controlled upper limb prosthesis offers the highest level of rehabilitation available today. Electromyography has been explained in detail in the next chapter.

In the past two decades, myoelectric control has attracted more and more attention for its application in rehabilitation and human-computer interfaces. In myoelectric control systems, arm gestures are often used for controlling peripheral equipments. Arm gestures are captured by surface electromyography using sensors which measure the activities of the muscular system. Accurate recognition of the user’s intent on the basis of the measured surface electromyogram signals is the key issue in the realization of myoelectric control.

The combined work of engineers and doctors has led to much advancement in biomedical engineering especially with the availability of computer system since 1985 which has provided new ways for analysis of myoelectric signal. These signals can be read by controller and motor can perform multiple actions as defined. Some of the unique contributions made by surface electromyogram include prosthetic arm control, robot-human relation with voluntary and non-voluntary reflex excitations *etc*. Measurement of generated limb force surface electromyogram is yet another advancement in this direction.

1.2 DIFFERENT TYPES OF PROSTHETIC ARMS

According to [*Galiano, 2007*] [*Micera, 2010*], there are many models of artificial arms which have occupied the market from time to time:

1.2.1 COSMETIC PROSTHESIS

Also called passive prosthesis, it replaces the missing part or limb and looks quite similar to natural one as shown in Figure 1.2. These are made of PVC, latex or silicon. They do not provide functionality, have light weight and require very little maintenance.

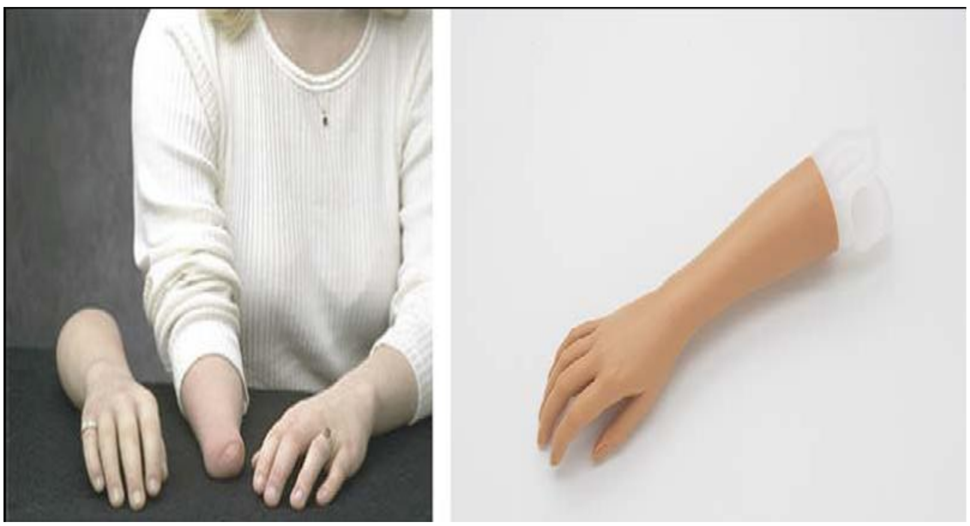


Fig. 1.2 Cosmetic Prostheses

1.2.2 BODY POWERED PROSTHESIS

These devices are functional prostheses that use some motion of the body to exert the force needed to control the prosthetic component. The basic components of this upper-limb prosthesis consist of socket, wrist unit, forearm section or extension, suspension and harness system (a Bowden Cable) having a hook or clamp at the end to secure the prosthesis and a terminal device or hand as shown in Figure 1.3. A Bowden cable consists of an inner core cable that is free to move within a sleeve cable which is fixed in place at either end. These devices require a harness, to be worn about the shoulders, to which one or more Bowden cables are attached. The conventional below-elbow, body-powered prosthesis has a single control cable that runs from the harness to a terminal device. Terminal-device opening and closing is then controlled by shoulder shrug and/or flexion of the residual upper arm. For an above-elbow amputee an additional control cable is used to control the harness for elbow flexion by unlocking the elbow.

Fig. 1.3 Body powered Prostheses

Body-powered prostheses are the most common kind of prosthesis used all over the world. The reason for their success is due to the intimate connection the control cable provides between the input and output. These prostheses are also lightweight, durable and of relatively low cost. They have an easy design, do not have problems with water or other external objects and require very little maintenance. Although generally successful, body-powered prostheses have a number of shortcomings. The major issues are the uncomfortable harness mechanism, the somewhat ungainly control motions, particularly in the case of above-elbow prostheses, restricted range of motion, limited load-lifting capacity and poor appearance.

1.2.3 ELECTRICAL PROSTHESIS

These are externally powered devices which receive their power from an electric source external to the body. These are a relatively new (last 20 to 25 years) addition to the armamentarium of prosthetic devices. The various components of an electrical arm are (Figure 1.4):

- **Touch Switches**

  A pair of touch switches remains in contact with antagonistic wrist muscles flexors and extensors. The wrist flexors activate the 'CLOSE' switch while extensors operate the 'OPEN' touch switch.

- **Control Circuit**

  The arm carries two limit switches in addition to touch switched. Each micro switch is connected to a Flip-flop which is configured to operate in set-reset mode. It is 'SET' by the touch switch and 'RESET' by the limit switch. The limit switches indicate the extremities of hand positions.

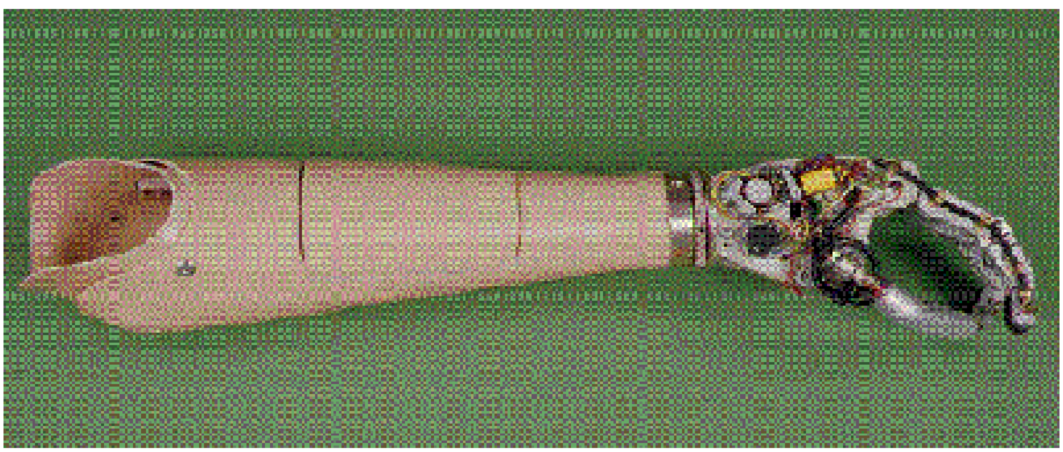


Fig. 1.4 Electric Prostheses

- **Control Relay**

  A semiconductor relay working at 6V / 9V operates the motor. When the flip-flop is having one polarity, DC voltage is applied by the relay to the motor such that motor rotates in one direction. When flip-flop output changes its polarity due to the operation of second touch switch, the relay also changes the polarity of DC voltage being applied to the motor and consequently, motor rotates in opposite direction. Thus the hand closes and opens.

Currently available electrical arms consist of an externally powered elbow and terminal device with the possible addition of a powered wrist rotator. The two most popular externally powered elbows are from Otto-bock Germany and Endolite, UK.

1.2.4 HYBRID PROSTHESIS

It combines the body actuated prosthesis with electrical prosthesis (Figure 1.5). Hybrid systems are used most frequently with persons who have amputations above the elbow or who have bilateral arm amputations. Such systems can provide the user with the high gripping and/or high lifting capacities of powered systems and the fine control of body power.

Fig. 1.5 Hybrid Prostheses

An example of hybrid control is illustrated in prosthetic limbs for persons with loss of both arms at the shoulder level. By providing the amputee with a body-powered limb on one side and an electric-powered limb on the other, they enable the wearer to use the limb that is most appropriate for a specific task. This method also enables the limbs to be operated independently of each other i.e. the body motions required to operate the body-powered side do not influence the state of the powered limb and vice versa; they are decoupled. These systems have the drawback that battery powered terminal device leads the forearm (harder to lift but good for long transhumeral amputation over the elbow).

1.2.5 MYOELECTRIC ARM

Myoelectric control derives its name from the electromyogram (EMG) signal, which is produced by a muscle when it contracts. There are two sets of muscles in the arm which get activated whenever an object is grasped or left by our fingers and are 180° apart. In myoelectric prosthesis, we make use of activation of these two muscles to open or close the terminal device. The electrodes accommodated in the prosthetic socket pick up the signals from these muscles which after conditioning are used to control the prosthesis. This type of system results in high grip force and grip speed (Figure 1.6).

Fig. 1.6 Surface EMG based Myoelectric arm

In the last decade, many electronic arms have been introduced in the market. Recently, advanced features like operation with muscle signal and proportional grip force have been added to the capabilities of these arms offering the user a wide choice to select a model according to his requirements.

Otto Bock [*Myobock, 1997*] has developed a variety of arms with different features so that an individual can select the arm which suits him best. The *Digital System* is designed to mimic the natural physiological control and function of the human body. This is the simplest designin which electrodes are located over the flexors and extensors of the residual limb; contractions of one muscle or the other close or open the hand.

Double channel System is useful when only one muscle site is available. In this arm, the hand opens or closes through one electrode only by making alternate contraction and relaxation of the same muscle group.

Grip Force System again uses two electrode sand offers two levels of gripping force control. With this system, a mild contraction of the flexor muscle closes the hand to a low force (approx. 10N) only. A stronger contraction of the same muscle builds grip force beyond this point.

Dynamic Mode Control system allows both grip speed and force to be proportionally controlled by both electrode sat all opening widths. The level of the muscle signal determines the gripping speed and force resulting in a more physiological gripping function. Such an arm has also been developed at CSIO Chandigarh.

1.3 BASICS OF ELECTROMYOGRAM

1.3.1 THE HUMAN MUSCLE

An electrical impulse that produces contraction of muscle fibers in the body is known as *myoelectric signal*. This term is most often used in reference to skeletal muscles that control movements. Each skeletal muscle consists of many fibre cells, which range in length from few millimeters (mm) to about 30 centimeters (cm) and have diameters of between 10 to 100 micrometers. Each muscle fibre is filled with smaller fibre called myofibrils which are packed with a highly ordered array of protein filaments. Nerve's message is carried by motor neuron from the brain and causes these filaments to interact, thereby making the muscle to shorten. Generally, the muscle will shorten to about 57% of their resting length during contraction and will achieve 70% of the resting length with more signals received [*Basmajian et al., 1985*] [*Online 4*] [*Online 5*].

Muscle contraction is a result of the stimulations from motor neurons. There are three types of muscle contractions: isometric, concentric and accentric [*Cram et al., 1998*]. In isometric contraction, the muscle is contracted while the length of the muscle is unchanged. These contractions are used in the postural control. Concentric contraction occurs when the length of the muscle shortens during the contraction. The amount of the available muscular energy in concentric contraction is less than the isometric contraction due to the energy loss related to the shorting of the muscle. Accentric contraction occurs when the length of the muscle increases during the contraction. The concentric and accentric contraction are also known as un-isometric contraction [*Singh, 2010*].

Motor neuron, axon, and all of the muscle fibers together form a motor unit. The number of muscle fibre per motor unit in a muscle is called the innervation ratio. Motor unit is established when the brain makes decision, for example, to move the arm and the nerve impulse that stimulate contraction carried in nerve by bundles of wire-like motor neuron from brain to muscle. When motor neuron is near to a muscle, it divides into several branches called axon terminals. Each muscle fibre in a motor unit is connected to each axon branch of the associated motor neuron at a point called neuromuscular junction (NMJ). The NMJ is located in a region in the middle of the muscle length called the innervation region. Combination of each motor neuron and the muscle fibers it stimulates is called a motor unit as shown in Figure 1.7.

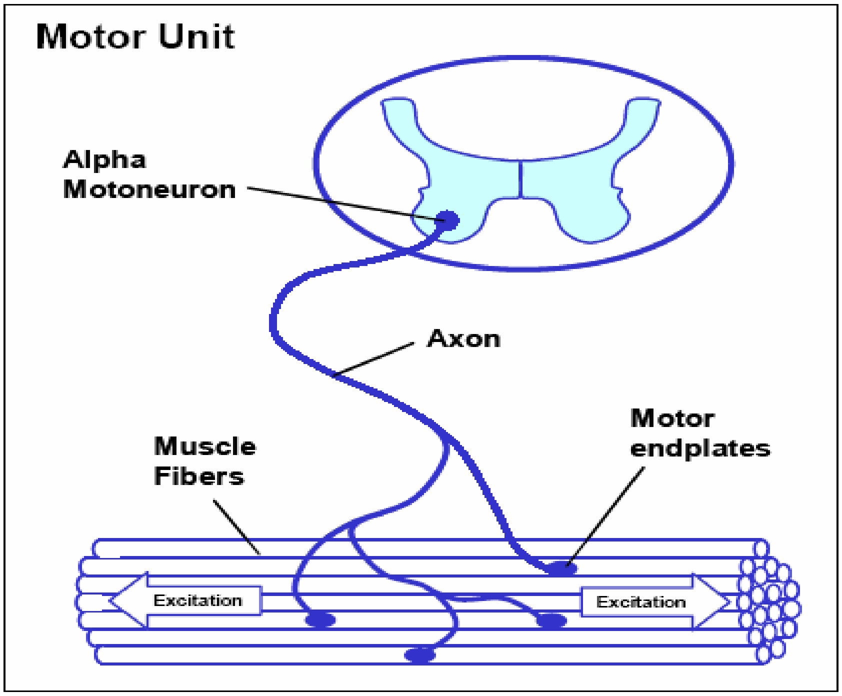


Fig. 1.7 Cross-section of skeletal muscle and connection to the bone via tendons

1.3.2 MOTOR UNIT ACTION POTENTIAL

The Motor Unit Action Potential (MUAP) is a compound signal reflecting the summation and cancelation of phases of the action potentials from individual muscle fibers in the motor unit. With intracellular recordings, the action potential is a monophasic waveform of about 100 mV, whereas the extracellular potential is a volume-conducted derivative of the rate of membrane depolarization. The Motor Unit Action Potential represents the spatial and temporal summation of these bi(tri) phasic spikes, wherein the negative spike in the normal muscle is obtained from two to three fibers within 0.5 to 1 mm of the electrode. The amplitude of the spike is determined by the proximity of the closest active fibers as indicated *by the fact that fibrillation potentials that originate from single fibers may have as high* amplitude as the Motor Unit Action Potential. The shape and duration of the Motor Unit Action Potential reflects the architecture of the motor unit. Recorded outside the end-plate region, the Motor Unit Action Potential typically has three phases: an initial positive phase, a negative spike, and a terminal positive phase. A negative after potential is sometimes recorded and is enhanced when the lower limiting amplifier frequency is set to 20 Hz. At the end-plate region the Motor Unit Action Potential is biphasic in shape with a sharp negative onset. In some instances, the Motor Unit Action Potential may be split up into four or more phases, reflecting a greater asynchrony of individual muscle fiber discharges [*Singh, 2010*] [*Lang, et al., 1973*] [*Thage, 1974*] [*Nikolic, 2001*] [*Nandedkar et al., 1984*] [*Morrish et al., 1999*].

Amplitude of the Motor Unit Action Potential

Because of cancelation between phases, the Motor Unit Action Potential amplitude is less than the sum of individual fiber potentials and may even be smaller than the amplitude of single fiber potentials. It depends on the proximity of the closest 2 to 15 fibers of the motor unit within about a 0.5-mm diameter and is proportional to the number and density of fibers in the motor unit. Because of the large effect of distance between the active fibers and the recording surface, the amplitudes of the Motor Unit Action Potential are markedly variable. The amplitude also depends on the type of electrode used. The amplitude is larger when using needle electrodes [*Nandedkar et al., 1985*] [*Stashuk et al., 2001*] [*Stegeman et al.,* 1999].

The amplitude increases as the radius of the muscle increases, and decreases proportionally as the distance between the active fiber and the detection site increase. The duration of the action potentials is inversely related to the conduction velocity of the muscle fiber, which ranges from 3 to 6 m/s. The relative time of initiation of each action potential is proportional to the length of each nerve branch, and the time that is taken for the depolarization to reach the pickup area. This relative time of initiation is inversely proportional to the conduction velocities of the nerve branches and the muscle fiber as well [*Cram et al., 1998*] [*Clancy et al.,* 1995] [*Deluca, 2009*] [*Olivo, 2010*] [*Kevin et al., 1985*] [*Buchthal et al., 1957*].

Shape of the Motor Unit Action Potential

Motor Unit Action Potential can be simple in shape or polyphasic. The latter is of long or short duration in myopathy depending on the degree of muscle fiber regeneration. It is important to calculate amplitudes and durations of simple and polyphasic potentials separately and to collect more Motor Unit Action Potential than necessary in case additional ones are needed [*Erik et al., 1994*] [*Merletti et al.*, 1995, 1999] [*Stulen et al.,* 1981].

1.3.3 THE ELECTROMYOGRAM

Muscle fiber action potentials are registered as a signal, which is the result of spatial-temporal superposition of the individual action potentials or motor unit action potentials (MUAPs). This signal is called electromyogram. If some muscle fibers, belonging to other motor units, are closer to the pickup area, their Motor Unit Action Potential will also be detected. However, the shape and amplitude of these muscle fibers Motor Unit Action Potential could be different. Therefore, it is not surprising that different shapes and amplitudes from different Motor Unit Action Potential are registered [*Lexell et al., 1986*] [*Deluca, 1997*]. It must be emphasized that the amplitude and shape of observed Motor Unit Action Potential are a function of the geometrical properties of the motor unit (active fibers related to the electrode), muscle tissue, detection electrode properties, amplifier properties, and filtering properties of the electrodeas shown in Figure 1.8.

The amplitude of the surface electromyogram is random in nature and can be represented as a Gausian curve. Measured surface electromyogram potentials range between 0 to 10 µV depending on the muscle under observation. It contains frequency components in range of 2 to 10 kHz with maximum signal power between 20 – 300 Hz for surface, and needs 1000 samples/sec or more sampling rate [*Basmajian et al., 1985*] [*Jung et al., 2007*] [*Knaflitz et al., 1991*] [*Arjunan et al., 2011*]. Aligning the electrodes along the muscle length close to each other results in an increase of higher frequency contents. There are three primary types of surface electromyogram visual displays: raw signal, spectral analysis, and processed signal.

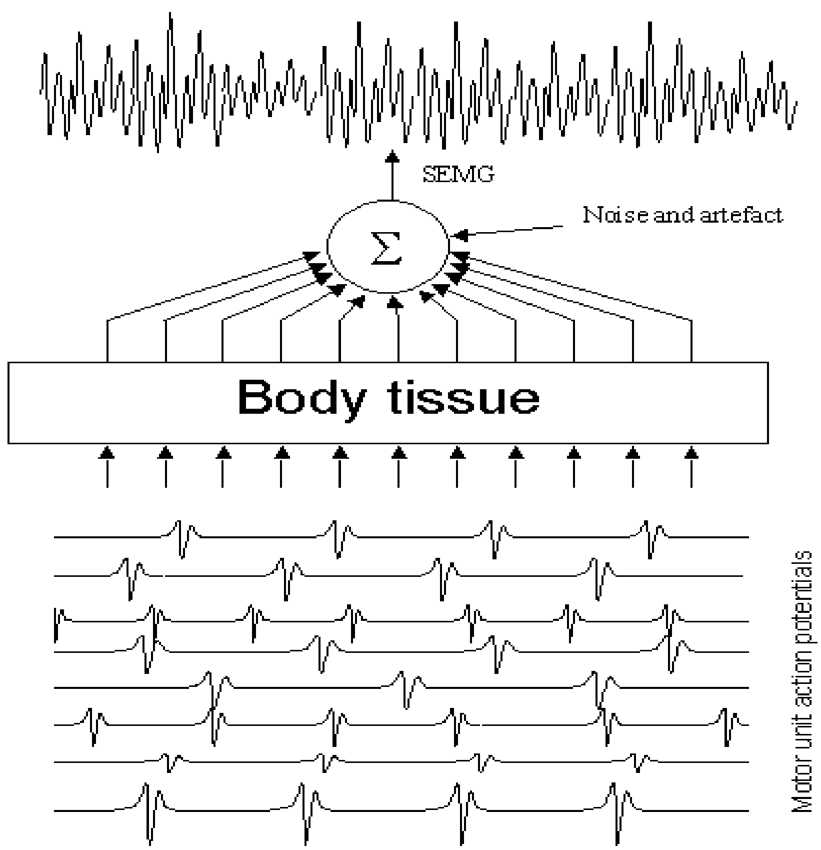


Fig. 1.8 Surface electromyogram as superposition of Motor Unit Action Potentials

Surface electromyogram signals are mainly studied for two applications, namely clinical (diagnostic) and Kinesiological (used in movement studies). Diagnostic surface electromyogram typically is performed by physicians, such as neurologists and physiatrists to evaluate the characteristics of the motor unit action potentials for duration and amplitude to diagnose neuromuscular diseases and injuries. Kinesiological electromyogram is used in kinesiology by physical therapists and ergonomists to determine the behavior of the muscles by analyzing the movements of patient. In this case surface electromyogram is studied for timing of muscle contraction, analyzing the function of the body movement and muscular actions, and to investigate the process of muscular fatigue [*Olivo, 2010*].

Some of the benefits of surface electromyogram are:

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

Physiological factors influence the surface electromyogram signal, including the quantity of tissue between the electrode and the surface of the muscle, the number of Motor Units Active Potentials, blood flow, fiber diameter, the depth and location of active fibers, fiber type composition *etc*. These factors vary independently among different muscles in the body. Other factors that influence the surface electromyogram signal are [*Mulla, 2011*]:

- Timing and intensity of muscle contraction
- Properties of the overlying tissue
- Properties of the electrode and amplifier
- Electrical properties of the contact between the electrode and the skin
- Distance of the electrodes for the active muscle area
- Gel material used on the electrodes

1.3.4 ELECTROMYOGRAM ELECTRODES

Needle electrodes

These are used by inserting through a small section of skin just beneath the surface and parallel to it. They reduce interface impedance and movement artifacts. Often these electrodes are planted to permit repeated measurements over an extended period of time. Needle electrodes for electromyogram, as shown in Figure 1.9, consist merely of fine insulated wires, placed so that their tips, which are bare, are in contact with the nerve, muscle, or other tissue from where the measurement is made. These types of electrodes are not used unless it is necessary to do so.

Fig. 1.9 Needle Elctrodes

Microelectrode

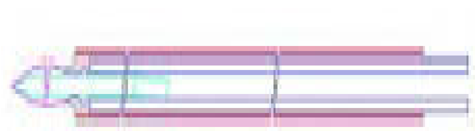


Fig. 1.10 Microelectrode

These electrodes are used to measure bioelectric potentials near within a single cell. Microelectrodes (Figure 1.10) are electrodes with tips sufficiently small to penetrate a single cell in order to obtain reading from within the cell. The tip must be small enough to permit penetration without damaging the cell.

Skin surface electrodes

They eliminate the requirement for cleaning and care after each use. Disposable electrodes are of floating type with simple snap connectors by which the leads, which are reusable, are attached (Figure 1.11). Although some disposable electrodes can be reused several times, their cost is usually low enough that for reuse is not warranted. They come pregelled, ready for immediate use [*Giroux et al., 1990*] [*Hermens et al., 2004*] [*Leslie et al., 2005*].

Fig. 1.11 Skin Surface Electrodes

Active electrodes

In most surface electromyogram readings passive electrodes are used. They are cheap, easy to manufacture and maintenance. They, however,require special skin preparation in the spot under electrode, and special pastes are required to lower impedance between electrodes and skin. Those requirements are usually acceptable, but not always welcome. Active electrodes are shown in Figure 1.12.

Fig. 1.12 Active electrode

Performance of active electrode is not affected as long as the electrolyte bridge maintains contact with metal and skins both. In recent years active electrodes have been introduced to eliminate the requirement of cleaning and care after each use. These are cheap, small in size and require no maintenance.

1.4 SURFACE ELECTROMYOGRAM PARAMETERS

Interpretation of surface electromyogram acquired through surface electrodes on underlying muscles can not be done by visual inspection of the signal. The parallelism between surface electromyogram signals and muscular activity in certain tasks presents a continuing challenge to define this relationship in relevant quantitative terms. During the past five decades, numerous attempts have been made to quantify this relationship. Clearly, if the surface electromyogram is to be a clinically useful index of the muscular force, it is necessary to develop an accurate means of quantification of predicting the relationship between an appropriate measure of the surface electromyogram signal and the corresponding muscle force [*Lindstrom et al., 1977*] [*Perry et al., 1981*] [*Kuba et al., 1992*] [*Zardoshti et al., 1995*] [*Lascu et al., 2007*] [*Ahsan et al., 2009*]. It has been felt that the signal has to be quantified in terms of parameters either in statistical, time or frequency domain. Several parameters quantified from surface electromyogram, which are correlated with muscular force relationship, have been put forward by researchers for identifying the performance of muscle activities for designing prosthetic device [*Chan et al., 2000, 2005*] [*Nakamura et al., 2004*] [*Phinyomark et al., 2009*] [*Merletti et al., 2009*] [*Farfan et al., 2010*] [*Ping et al., 2011*] [*Kwon et al., 2011*] [*Zhang et al., 2010*] [*Rafiee et al., 2011*] [*Sobahi et al., 2011*] [*Shivling et al., 2012*] [*George et al., 2012*] [*Ibrahimy et al., 2013*] [*Xu et al.,* 2013, *2014*]. These parameters are categorized in Figure 1.13.

Since the the most common approach for controlling active prosthetic devices is through parameters of surface electromyogram signal, the performance of surface electromyogram signal analysis, along with hardware implementation, encourages its applications related to prosthetic devices and human computer interactions.

In recent years, detecting upper-limb motion intention for prosthetic control has attracted growing research. However, the difficulties in surface electromyogram signal classification for prosthetic applications lie in the selection of electrode locations on the arm, signal processing and the extraction of a feature vector capable to classify several motions. The detailed performance of aforesaid feature parameters before designing and developing prosthetic device will be carried out in next two chapters.

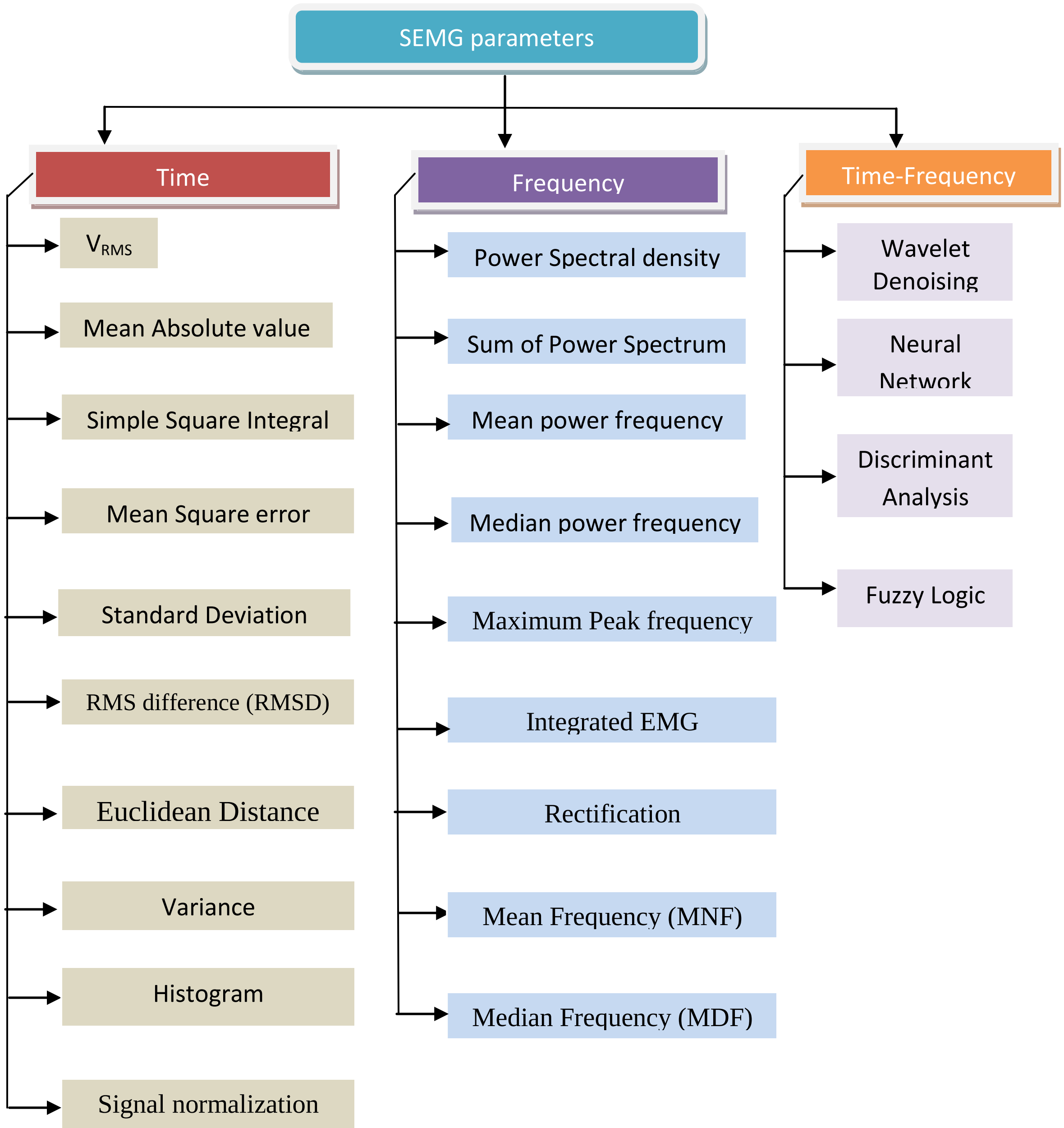


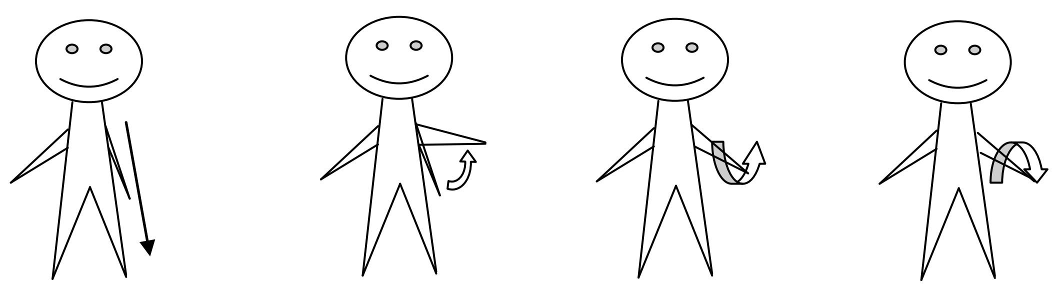
Fig. 1.13 Surface Electromyogram parameters for the prediction of effectiveness of recorded data

1.5 OBJECTIVES OF THE PRESENT WORK

The main objective of this work is to design a prosthetic device similar in size to the natural one with controlled movements to fulfill variable grip requirement. To meet this aim, it is imperative to explore various methodologies and algorithms meant for classifying surface electromyogram signal existing at different muscles of the arm for the purpose of interpreting the signal corresponding to different arm motions shown in Figure 1.14. The aim also includes the testing of the designed prosthetic arm on different amputees.

Specifically, the action points may be enumerated as:

1. To develop electrode system for acquiring SEMG data from above-elbow amputees.
2. To simulate and analyze stored SEMG for different postures from three classes of above-elbow amputees.
3. To compare the actual SEMG with simulated model and verify the results with the help of soft computing techniques.
4. To design and develop electronic circuitry / mechanical structure for development of prototype model of 4 DoF prosthetic arm.



(a) Motion P1 Rest   (b) Motion P2 Flexion   (c) Motion P3 Abduction   (d) Motion P4 Adduction

Fig. 1.14 Different arm movements performed by subjects

1.6 ORGANIZATION OF THE THESIS

The thesis consists of six chapters including background and literature survey. Chapter 2 through 7 of the thesis concentrates on the investigative experiments leading to above elbow prosthetic development:

Brief description of different chapters is as follows:

Chapter 2 briefly discusses the various methods and algorithms used by researchers to implement above-elbow prosthesis.

Chapter 3 gives research protocols adopted during the study. Placement of electrodes for acquisition of surface electromyogram has been explained. Details are given on the motions performed by each subject. The required hardware and software to acquire surface electromyogram signal and its signal conditioning have been explained. Details of computation of surface electromyogram parameters after removing different artifacts have also been discussed.

Chapter 4 discusses the methods of processing and analyzing surface electromyogram signal from biceps and triceops muscles for extracting amplitude related parameters for characterizing upper arm motions besides the statistical analysis. Because of subtle intricacies among the data, the potential findings from the statistical analysis of the data are considerable. To validate the effectiveness of quality of surface electromyogram, repeated factorial analysis of variance technique was implemented.

Chapter 5 first describes a comparative study to evaluate the wavelet denoising for optimal motor unit action potential detection through the decomposition based on the different wavelet functions of Daubechies, Coiflet and Symmlets families. It also reports techniques for classification of sEMG signal for class separability of different upper arm motions using Linear Discriminating Analysis and Artificial Neural Network pattern classifier approaches.

Chapter 6 presents the developed prototype of above-elbow myoelectric arm. The implementation includes design, fabrication and testing of electronic processing circuit, socket and mechanical hand. The design was carried out keeping in mind the factors like reliability, light weight, variable grip force with ease of attachment for simple operations like opening, grasping and lifting objects of different weight with grip force slightly more than enough just like that of a natural hand.

Chapter 7 gives conclusion arrived at after overall exposure to the techniques of analysis and classification of sEMG signal. Limitations of the study have been listed. Finally, potential directions for future research work have been discussed.

2

LITERATURE SURVEY

Human body is an ingenious result of evolution. Intelligent prosthetic devices using computerized system and minimal user input cannot yet mimic the human range of motion. New technologies are making it increasingly possible to restore partial functions of hand. Surface electromyogram signals present an interesting solution to control artificial hands because they are easy to record and allow the user to control different arm motions. After limb amputation, natural complex muscles' signal processing is no more available to control the prosthetic device and for this reason complex pattern recognition approaches have to be developed to interpret the voluntary commands by the user. Also, the additional feature for a remote controlled elbow joint motion system controlled by other hand for improving degree of freedom is very much required. The development of the prosthetic arm has a long history.

[*Tomovic et al. 1962*] described the design of an artificial limb by using different point of departure. This work exploited all the possibilities of the principles described in the paper. An important improvement would be to divide the sensitivity elements into layers. The first layer would react to cutaneous effects, while the second layer would control the power output. Much greater sensitivity will, thus, result than the first experiments showed. Such a hand is capable of supplying information in electrical form which is used in a kind of biological response to inform the patient about the various aspects of the object touched by the hand. Thus, a new dimension is added to the artificial hand.

[*Graupe, 1978*] described a prosthesis control system based on microprocessor hardware for the control of an artificial limb for above elbow amputees accomplished in several degrees of freedom. The design employed time series identification techniques for parameter discrimination. System involves one set of electrodes for discriminating and controlling five limb functions. The system feeds to a motor control and actuation unit identical to that of the toe-controlled system which is presently used by a bilateral above-elbow amputee.

[*Ray et al., 1983*] stated that most of the theoretical studies relating the surface electromyogram with muscular force suggest that the amplitude of the surface electromyogram should increase proportionately with the square root of the tension. However, direct experiments have shown an almost linear relationship. Also, according to him, variations in action potential magnitudes and firing frequency have not been taken into account. However, recent physiological experiments have made it feasible to correlate various parameters. If these mathematical correlations are incorporated in a model, the linearity between the surface electromyogram and the muscular force is greatly improved.

[*Gibbons et al., 1987*] use surface electromyogram signals from residual muscles to control above-elbow prosthesis but present many problems under open-loop control. A more satisfactory control technique was the extended physiological perception where the inherent response exists within an intact joint to provide closed-loop control. A choice from a range of linkages can enable the user to perform different tasks in different situations.

[*Kuba et al., 1992*] described the flexible grasping motion control for a hand with two fingers. To control, the reference grasping force was decided in advance by the operation and the property of the reference grasping force. The way to extend the grasping control by including the operator in to the control loop was also explained. The study was carried out to know the interface between human and an artificial hand based on human being's traits.

[*Neill et al., 1994*] obtained data from remnant muscles in residual upper limbs of amputees and intact muscles of healthy subjects. Spectral parameters (mean frequency, median frequency, and equivalent statistical bandwidth) of the myoelectric signals were calculated and examined for significant differences between the remnant muscle data and intact muscle data. Other factors were examined for possible significant effect on the spectral contents of the myoelectric signals. Although no pattern of spectral difference between the myoelectric signals of residual versus intact limb muscles was found, spectral differences were apparent by visual inspection in most cases.

[*Clancy et al., 1995*] demonstrated that temporal whitening of individual surface electromyography waveforms and spatial combination of multiple recording sites improve the performance of surface electromyogram amplitude estimation. A phenomenological mathematical model of multiple sites of the surface electromyogram waveform, with analytic solution for an optimal amplitude estimate, is presented. Experimental surface electromyogram waveforms were then sampled from multiple sites during non fatiguing, constant-force, isometric contractions of the Biceps or Triceps muscles.

[*Fang et al., 1999*] developed a comprehensive technique to identify Single Motor Unit Potentials (SMUP) and to decompose overlapped surface electromyogram signals into their constituent potentials. This technique was based on one-channel surface electromyogram recordings and was implemented for many clinical surface electromyogram tests. It measures waveform similarity of potentials in the wavelet domain, which gives this technique significant advantage over other techniques. It also classifies spikes based on the nearest neighboring algorithm, which is less sensitive to waveform variation.

[*Fermo et al., 2000*] presented the development of a sensor for detecting human muscle contraction, which captures myoelectric signals, to control a myoelectric prosthesis of superior limb. The analysis of the signal is carried out through software running in a microcontroller that decides to open or close the artificial hand. The facility in changing the acting form by software makes its use attractive for the patient.

[*Morita et al., 2001*] presented a new approach for controlling the prosthetic hand through the torque control of each joint. The joint torque is estimated from surface electromyogram signals using Artificial Neural Networks (ANN). The learning system is based on feedback error learning.

[*Venkataramanan et al., 2004*] used myoelectric control signals in the operation of devices external to the human body. A variety of myoelectric control algorithms exist but there is immense scope for optimization. This paper proposes an intelligent system which is capable of optimizing the system speed and the number of actions that can be selected. Such optimization involves rigorous mathematical analysis of the characteristics and the interdependence of these two parameters. The intelligent systems employ a technique for continuous monitoring. Accordingly, they allocate the least selection duration to those actions which are to be executed a number of times.

According to **[*Chappell, 2005*]**, loss of a natural hand means that the neural connections between the brain and the palm, fingers and thumb are also lost, including any feedback paths e.g. sensing temperature. In this research, the author is having an artificial hand with sensors allowing for the inclusion of automatic control loops, freeing the user from the cognitive burden of object holding. According to the authors of this paper, force, object slip and finger positions are the variables that need to be measured in a hand designed for the physically impaired person. A high specification is required for any sensor design.

[*Al-Assaf, 2006*] collected myoelectric signals from five subjects including male and female between the age group of 20 – 44 years. All members of the human test group were free from any apparent neuromuscular problem. Myoelectric signals were recorded using Ag-AgCl surface electrodes from biceps and triceps brachii as these muscle groups are related to the elbow and wrist movements of interest.

[*Reaz et al., 2006*] brought out the point that surface electromyogram signals acquired from muscles require advanced methods for detection, decomposition, processing and classification. This paper illustrates the various methodologies and algorithms for surface electromyogram signal analysis to provide efficient and effective ways of understanding the signal.

[*Roberson et al., 2007*] considered externally powered upper extremity prosthesis as a system in which the necessary components were viewed and divided into four subsystems: input, effecter, feedback and support. Each subsystem performs its own task but was related to other and together all subsystems function as prosthetic device to provide the movement to the amputee.

[*Ryait et al., 2009*] describe the process of improvement of prosthetic devices. It deals with the mathematical models developed till now for surface electromyogram signal analysis. Different design approaches have been reviewed for artificial hand. One of the approaches discussed is on the body-powered terminal devices which are controlled by the user’s pull on the control cable to open the hand or hook and for the grip strength. Another alternative is myoelectric control type, an externally powered system which uses electrical impulses, generated by contraction of the amputee's own remaining muscles to operate a motor in a mechanical hand, hook or elbow.

[*Toledo et al., 2009]* designed a myoelectric prosthetic arm to interact with the amputee. Traditional commercial prosthesis with three degrees of freedom was reported. Four kinds of prosthesis were presented: Boston Elbow, Utah Arm, Kuiken's Prosthesis within DARPA's Project and prosthesis under development in laboratory.

[*Ryait et al., 2010*] established that the analysis of the surface electromyogram signal depends on a number of factors like amplitude, time and frequency - domain properties. The study of signals at different below elbow muscles for four different operations of the hand was done. Myoelectric signals were extracted by using a single-channel surface electromyogram amplifier consisting of a differential amplifier, non inverting amplifier and interface module. MATLAB softscope was used to acquire the surface electromyogram signal from the hardware. After acquiring the data from six selected locations, interpretations were made for the estimation of limits of the surface electromyogram using the MATLAB-filter algorithm and the Fast Fourier Transform technique.

[*Kumar et al., 2012*] discussed grip force based complete design and development of myoelectric arm. According to them, in order to extract spectral components that contain important information, electrodes' placement as far as possible from each other in transverse direction is necessary.

[*Hariharan et al., 2012*] have presented a comparative study of different wavelet families for analysis of electromyogram signal. The work related to feature extraction and classification protocols for wrist operations from forearm muscle signal has also been reported.

[*Veer et al., 2013*] extracted myoelectric signals from above elbow using self-designed hardware system. Surface electromyogram data from selected locations of above elbow was processed for various feature extractions using LABVIEW for root mean square computation. Result shows characteristics change in extracted feature values for different movements with respect to each position and movement.

[*Lazaro et al., 2014*] applied Independent Component Analysis (ICA) to separate mutually independent components of surface electromyography signals which provided a promising method for the classification of hand action movement based on each level of muscle contraction.

[*Kwon et al., 2014*] investigated the variation in human movement stability while the amount of surface electromyogram based assistive power was changed. A robotic device provided a torque that was proportional to the torque estimated by surface electromyogram for assisting human movements. 12 volunteers participated in the elbow flexion experiments. The maximum finite time Lyapunov exponent, the average logarithmic rate of the divergence of neighboring trajectories, and the variability of the kinematic data were used to quantify the stability of the assisted elbow movements.

Many researchers have worked on muscle control algorithms and classification of sEMG signal so that myoelectric prosthesis can be used effectively. The decomposition procedures consist of a series of algorithms that are successively and iteratively applied to resolve a composite surface electromyogram signal into its constituent motor unit action potentials before its evaluation. The chapter presented evaluation and interpretation of surface electromyogram signals and pattern recognition method for more accurate identification of upper arm motion command. The classification result based on statistical technique is able to accommodate expected individual differences and requires less computing time in the pattern recognition with the extracted feature parameters. Various mathematical techniques and Artificial Intelligence [*Toledo et al., 2009*] [*Deluca et al., 1986*] [*Ryait, 2011*] [*Srhoj et al., 2011*] methods have received extensive attention. Mathematical models include Wavelet Transform, Time-Frequency approaches, Fourier Transform, Wigner-Ville Distribution, the smoothed Wigner-Ville, Statistical Measures and Higher-Order Statistics with another parameter like Median Frequency (mf) *etc*.

3

METHODOLOGY, PROTOCOLS & SEMG SIGNAL ACQUISITION

3.1 SURFACE ELECTROMYOGRAM (SEMG) RECORDING PROTOCOLS

Since the objective of this study was to investigate the muscular force relationship based on different contraction activities, the study was conducted on three different classes/groups of amputee volunteers according to the scheme of Figure 3.1.

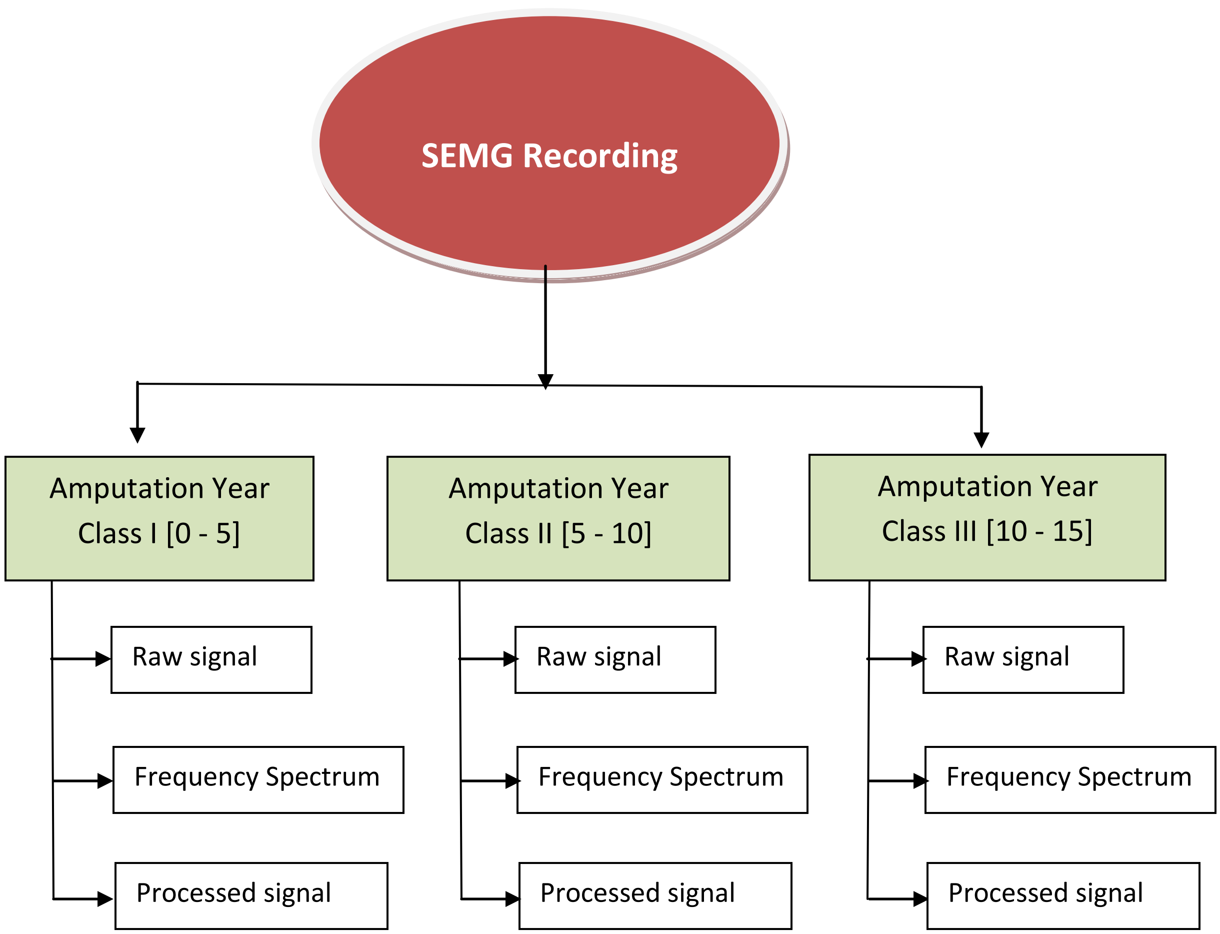


Fig. 3.1 Surface electromyogram recording protocol

3.1.1 PARTICIPATING SUBJECTS

A total of twenty amputees participated in the complete part of study, out of which:

a) Fifteen amputee volunteers, age 21-58 years, weight 55-80 kg, height 160 to 179 cm having active residual stump participated as subjects in the study of EMG signal.

b) Five amputee volunteers, age 22-31 years, weight 54-85 kg, height 166 to 178 cm with residual stump disorder participated as subjects in second part of study especially for denoising purpose.

All participating amputee volunteers, with different categories of Body Mass Index range [*Jamal et al., 2011*] [*Online 6*] having active residual stump (or right/left arm above elbow muscular disorder) and no history of neural disorders participated as subjects in this study (Table 3.1 and Table 3.2). All of the participants read and signed an informed consent prior to conducting the experiment.The surface electromyogram signals were recorded from their residual muscles with repeated experiment with each muscle movement. The participants were asked to perform the muscle contraction test at least three times with different activity efforts. The participants were allowed a five minute rest period between the tests to minimise the potential effects of fatigue (from one subject to another and so on).

Table 3.1 Detail of amputee subjects (used for prosthetic interpretation and design)

Sr. No.	Subject ID	Amputation year	Weight (kg)	Height (cm)	BMI (Kg/m^2)
1	2011SEMG- ADS 001	5	61	5’8”@ 173 cm	20.4
2	2011SEMG- ADS 002	12	62	5’6” @ 167 cm	22.23
3	2011SEMG- ADS 003	15	57	5’8”@ 173 cm	19.05
4	2011SEMG- ADS 004	4	78	5’5” @ 165 cm	28.65
5	2011SEMG- ADS 005	8	63	5’6” @ 167 cm	22.6
6	2011SEMG- ADS 006	10	76	5’8”@ 173 cm	25.4

7	2011SEMG- ADS 007	7	78	5’8”@ 173 cm	26.1
8	2011SEMG- ADS 008	3	53	5’7”@ 170 cm	18.3
9	2011SEMG- ADS 009	11	72	5’8”@ 173 cm	24.1
10	2011SEMG- ADS 0010	2	60	5’7”@ 170 cm	20.8
11	2011SEMG- ADS 0011	7	75	5’10”@ 178 cm	23.7
12	2011SEMG- ADS 0012	9	66	5’8”@ 173 cm	22.1
13	2011SEMG- ADS 0013	10	67	5’7”@ 170 cm	23.2
14	2011SEMG- ADS 0014	12	70	5’7”@ 170 cm	24.2
15	2011SEMG- ADS 0015	3	79	5’8”@ 173 cm	26.4

Table 3.2 Detail of amputee subjects (used for denoising)

Sr. No.	Name	Weight (kg)	Height (cm)	BMI (Kg/m^{2})
1	2011SEMG- RADS 001	61	5’8” @173 cm	20.4
2	2011SEMG-RAD S002	75	5’10”@ 178 cm	23.7
3	2011SEMG- RADS 003	53	5’7”@ 170 cm	18.3
4	2011SEMG- RADS 004	79	5’8” @173 cm	26.4
5	2011SEMG- RADS 005	60	5’7”@170 cm	20.8

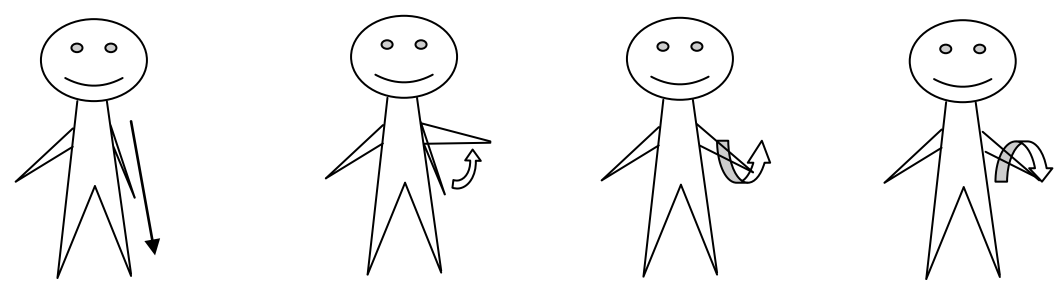
3.1.2 ACTIVITIES PERFORMED

For the surface electromyography, the designed double channel acquisition system was used, and the following procedures were performed:

- Use of dual pair of electrodes distributed on the biceps brachii and triceps brachii muscles simultaneously;
- Placement of the reference electrode on the forehead of the volunteers;
- Use of the Labview 2011 with data acquisition card (DAQ-6024 E) for recording and signal analysis;

All of the measurements were performed as the subjects sat erect in a rigid chair furnished with an approximately vertical backrest and were asked to perform four upper arms independent movements namely elbow extension, elbow flexion, abduction and adduction as described. The arm was moved from rest position (0^o) to an angle of 45^o - 60^o with maximum muscular dynamic contraction for elbow flexion movement. Similarly arm was moved from rest position (0^o) to maximum voluntary contraction (90^o) with abduction and adduction movements respectively.

Dual channel experimental acquisition set up was used. Each subject was asked to perform four independent movements for different muscles activation with maximum epoch time of 3s for each movement respectively shown in Figure 3.2.



(a) Motion P1 Rest   (b) Motion P2 Flexion   (c) Motion P3 Abduction   (d) Motion P4 Adduction

Fig. 3.2 Different arm movements

- Activity P1- Arm was in rest with downward position parallel to body. This position is called arm extension.

- Activity P2- Arm was moved upside. This action is called flexion elbow.
- Activity P3- Arm was moved voluntarily from rest position (0^o) to maximum position (90^o) giving abduction direction.
- Activity P4- Arm was rotated in adduction direction i.e. from rest position (0^o) to maximum muscular contraction position (90^o).

3.1.3 ELECTRODES PLACEMENT

The experimental surface electromyogram signal was acquired from spontaneous two upper-arm biceps and triceps brachii muscles simultaneously through non invasive electrodes placed on the midline of muscle belly (Figure 3.3) individually with maximum epoch time of 3s using data acquisition card (6024 E) and soft scope based simulated code. Simple form of superficial pre-gelled Ag/AgCl electrodes (five electrodes) with bipolar configuration (two independent channel pairs and one reference electrode) were used. The two electrodes were placed on right upper arm muscles separated by interelectrode distance of 1 cm while reference electrode was placed on forearm at a distance of 5 cm. The reference electrode (at times called the ground electrode) is necessary for providing a common reference to the differential input of the preamplifier in the electrode.

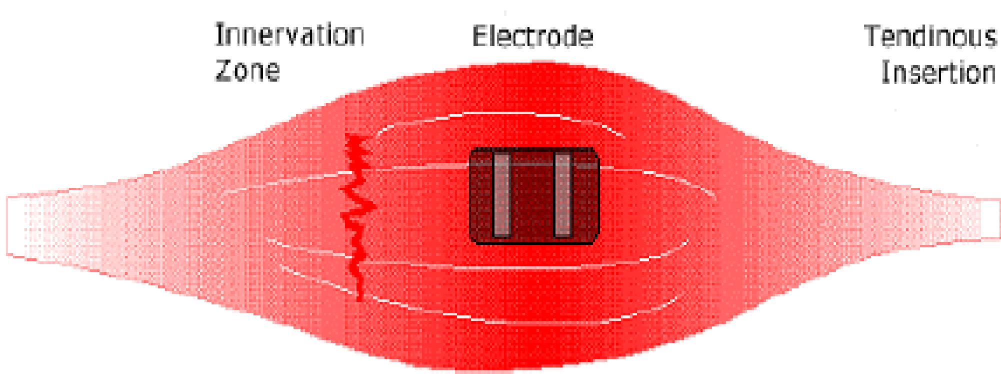


Fig. 3.3 The preferred electrode location is between the motor point and the tendinous insertion, with the detection surfaces arranged so that they intersect as many muscle fibers as possible [*Deluca, 2002*]

With the bipolar electrode the optimal position of the electrodes is parallel to the muscle fibers in order to maximize the probability of proper signal acquisition.

3.2 SURFACE ELECTROMYOGRAM SIGNAL ACQUISITION

A typical data acquisition session consists of following steps:

1. Initialization of the soft scope interfacing.
2. Configuration: Adding channels and controlling acquisition protocols.
3. Execution: Acquiring signal and sending data to workspace.
4. Termination: Completion of data detection process after 3 seconds.

Measured surface electromyogram potentials range between 0 to 10 µV depending on the muscle under observation. It contains frequency components in range of 2 to 10 kHz with maximum signal power between 20 – 300 Hz, and needs 1000 samples/sec or more sampling rate [*Kumar SMA, 1996*] [*Knaflitz et al., 1991*]. Aligning the electrodes along the muscle length close to each other results in an increase of higher frequency contents. Electrode impedance should be as low as possible but not more than 2 kΩ. The difference signal between reference and active electrode was processed to reduce noise in the system [*Kumar et al., 2012*]. The signal is random, very small in amplitude and mixed with noise of different frequencies.

For better contact between electrode and muscle, a jelly type conducting solution was used. Experiments were made to optimally place these electrodes and to identify the proper point of axial spread of muscle where the amplitude of signal was maximum. The electrode assembly cannot be placed axially along the muscles of the arm because the stump length available from such patients is generally not enough. The placement of this assembly in the transverse direction led to the difficulty that the surface of arm was not uniform throughout the radial span of the stump; it was rather curved. Also at the time of relaxation and contraction of the muscle, this curvature varies and the electrodes could not be fixed properly to pick the signal from a particular point.

During experiments with this assembly, it was noted that if electrodes are placed very close to each other, active and reference electrodes pick up almost the same signal from the same muscle, so for this reason, to get substantial signal, we placed the electrodes as far as possible from each other in the transverse direction.

3.3 EMG SIGNAL PROCESSING

Amplifiers suitable for biomedical applications must usually have a high common mode rejection and a high differential input resistance. Although several integrated circuit operational amplifiers possess these qualities, it has been difficult to obtain satisfactory performance with respect to the surface electromyogram properties in practical circuits. Advent of modern electronics and the process of differential amplification have enabled the measurement of surface electromyogram signals of low noise and high signal fidelity. With differential amplification, it is now possible to measure the full effective bandwidth of the surface electromyogram signal. There are several important properties to consider in a pre-amplifier:

- High common mode rejection ratio
- Very high input impedance
- Short distance to the signal source
- Strong DC signal suppression

In the present research work, the surface electromyogram signals were detected with the dual channel differential-mode operational amplifier (INA 126) in first stage having a gain of 5 and common mode rejection ratio (CMRR) greater than 90 dB. The signal was again amplified by an inverting amplifier (LM 358) in second stage with a gain of 1000. The purpose of the inverting amplifier was to provide fine tuning of the gain needed. The surface electromyogram signals were acquired from two upper-arm Biceps and Triceps Brachii muscles simultaneously with maximum epoch time of 3s using data acquisition card (6024 E) and soft scope based simulated code [*Veer, 2014*]. The schematic of the senor system used for data acquisition is shown in Figure 3.4.

Softscope

Soft scope is a graphical user interface for selecting and configuring data acquisition sources in LABVIEW and then acquiring, viewing, and analyzing data using a familiar, oscilloscope-like interface. Soft scope quickly verifies hardware operation and performs live data analysis using a library of built-in measurement functions. Soft scope was extended with the analysis functions and export data from soft scope to the LABVIEW workspace.

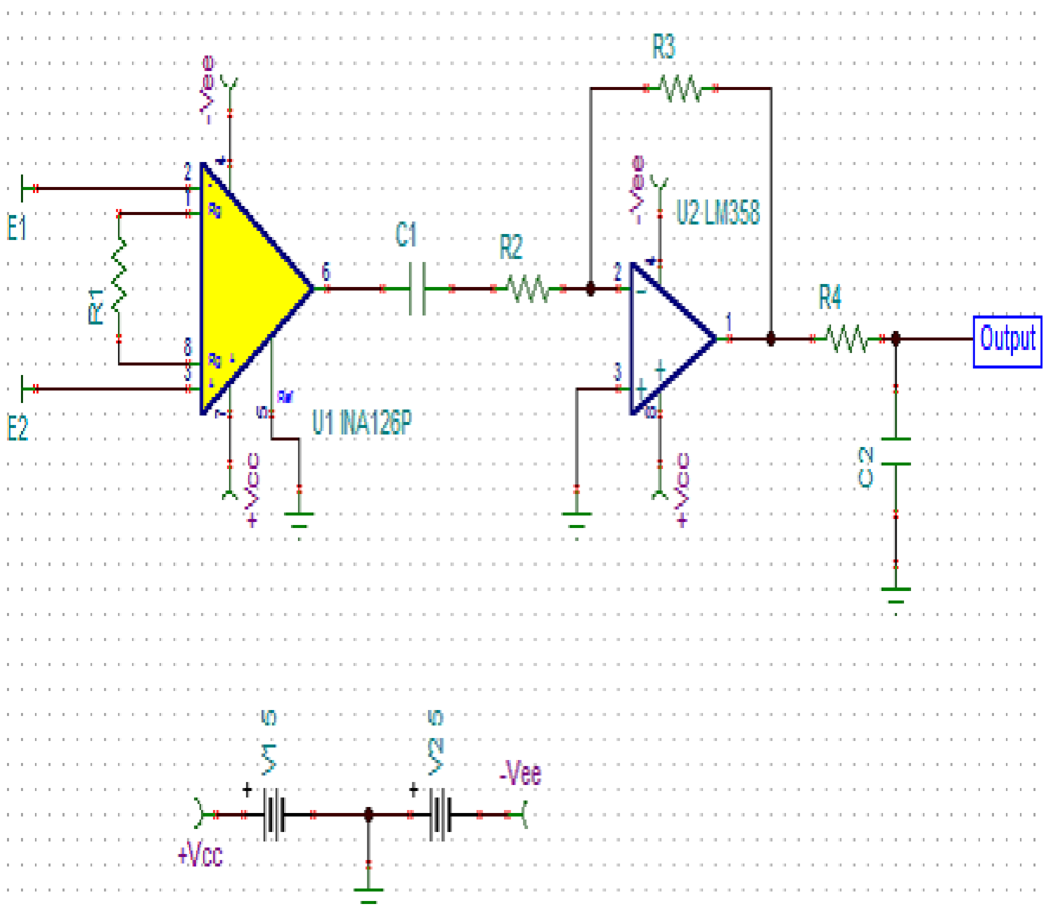


Fig. 3.4 Schematic of the designed sensor system for data acquisition

The value of sampling rate, configuration of channels, location where data is stored, data in which form was configured and implemented using computation simulated code is presented in Figure 3.5 and its front panel is shown in Figure 3.6. The sampling frequency used for the acquisition was 1000 Hz. In the next stage, interfacing was done to connect the surface electromyogram signal amplifier circuit to the computer through data acquisition card (DAQ). The process of digitization followed the concept of the sampling frequency, as it is based on Nyquist frequency theorem i.e. the process of sampling the surface electromyogram signal at less than 1000 Hz (samples/second) may distort the signal due to aliasing.

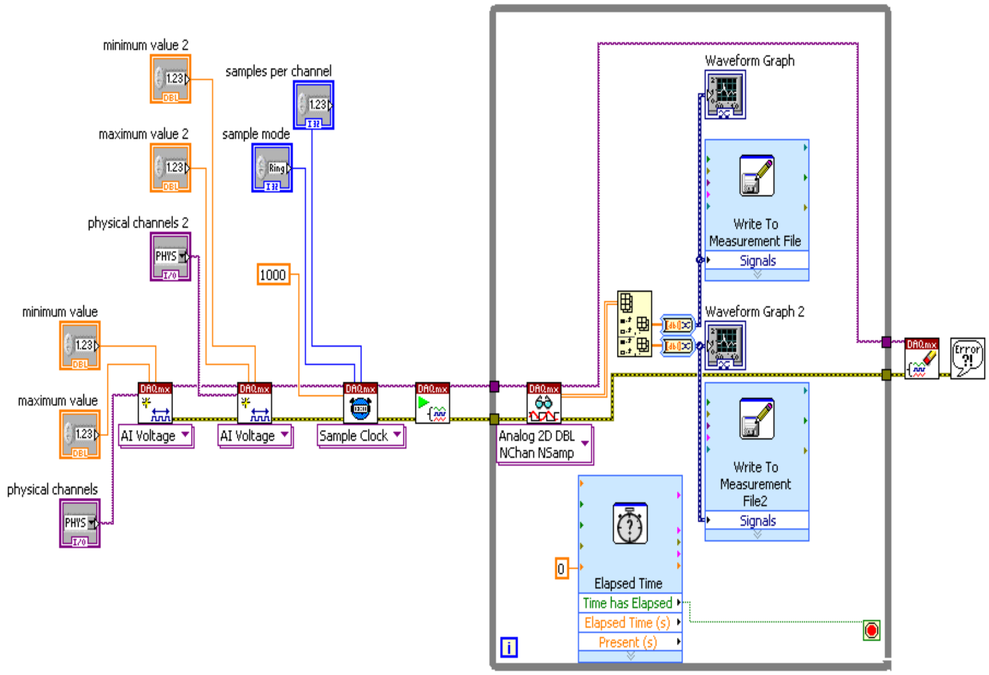


Fig. 3.5 Computer aided simulated code for signal detection from multi channel system

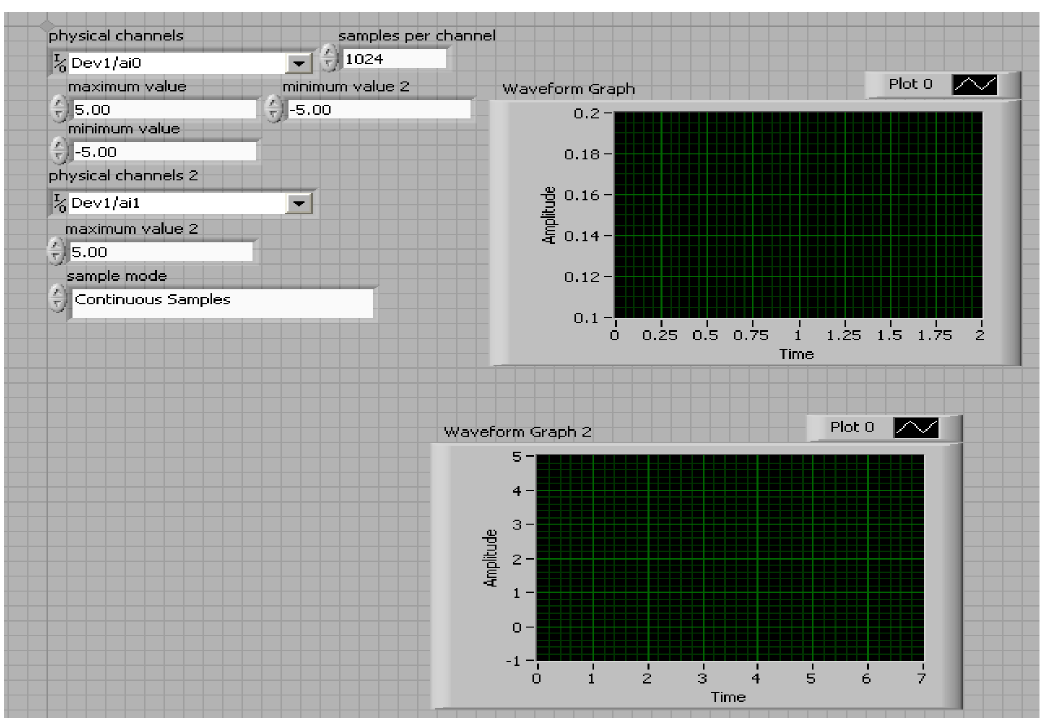


Fig. 3.6 Front panel for signal detection from multi channel system

Softscope based simulated code was exercised for investigating the nature of recorded surface electromyogram before its interpretation.

Some of the noise from the detection and recording equipment cannot be eliminated, but can be reduced using high quality components. Ambient noise of about 50 Hz comes from power sources. Next, the noise from motion artifacts has most of its energy in the frequency range of 0 to 20 Hz and can be reduced by proper design of electrical circuit. As far as electrode configuration is concerned, bipolar is more appropriate than unipolar configuration since it eliminates the unwanted signal. This bipolar configuration serves as a band pass filter whose bandwidth is a function of the spacing between the [*Olivo, 2010*] detection surfaces. The complete experimental setup is shown in Figure 3.7.

3.4 PRECAUTIONS TAKEN

Keeping in view the patient safety, artifacts due to noise/interferences and for the recording of authenticated surface electromyogram data [*Majewski et al., 1984*] [*Komard, 2005*] [*Kumar, 2012*], following issues were considered.

- While taking surface electromyogram (SEMG), electrostatic and electromagnetic disturbances are themain source of interference. A single common earth point for instrument was used to avoidground loop currents;
- Shielded cables were used between electrodes and the amplifier toimprove signal-to-noise ratio;
- Electrodes and leads were fixed firmly over the skin of muscle under supervision to avoid low frequencycomponents in the signal;
- Electrodes were secured and placed withconductive gel;
- Viscosity of the paste used for sticking electrodes to the patient was keptoptimum. If the paste were relatively dry, it does not make good ioniccontact with the skin. This was verified from the impedance valuebetween electrode and body ground time to time and was kept less than 2K;
- Saline or clinical spirit was thoroughly mixed with the paste whenevervalue of this impedance increased;
- To eliminate subjectivity, all the recordings were done by the same personnel;

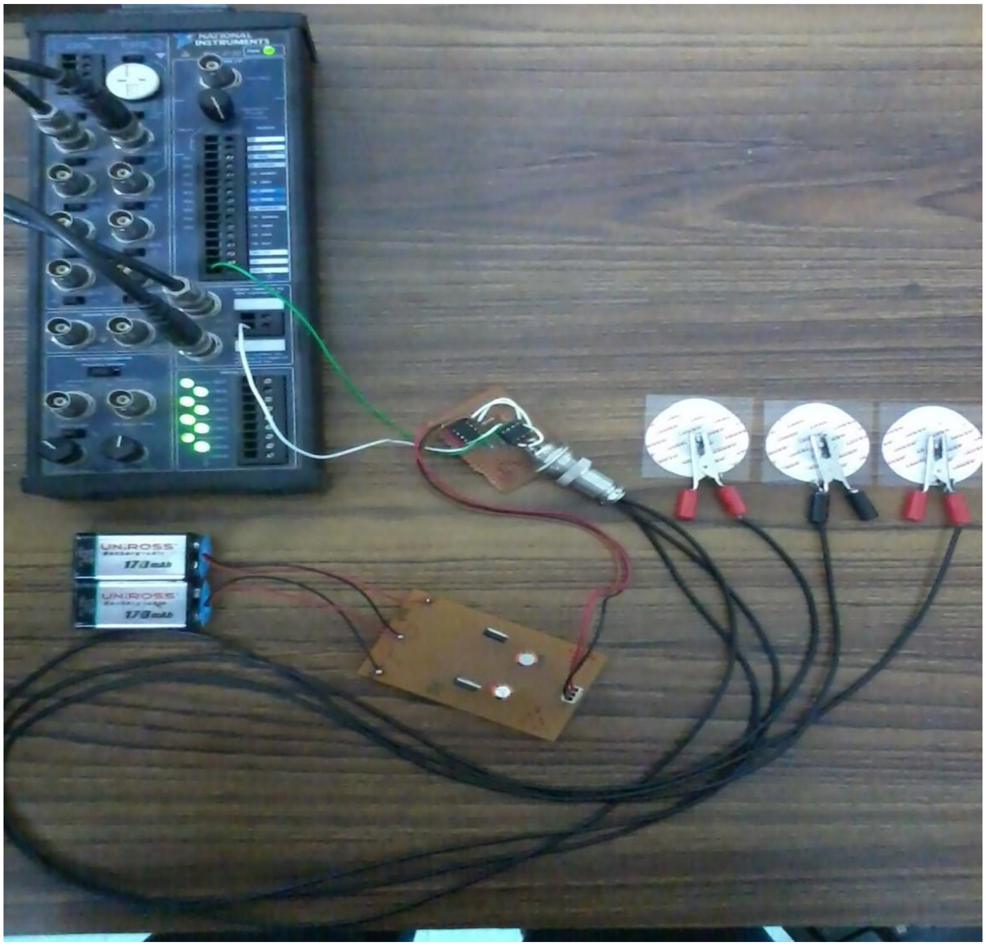


Fig. 3.7 Complete experimental set up

- Volunteers/Subjects were asked to keep their eye closed and were not allowed to talk so that artifact free surface electromyogram data can be recorded;
- During whole experiment, the unwanted electrical appliances were kept off or kept away from experimental setup to avoid the electromagnetic noise in signal;
- Means of wireless communication such as mobile phones are kept away or switched off during signal acquisition;
- Subjects were asked not to move their head as this causes wires to move which are connected to electrode. The movements of wires are also contributor of noise in signal.

4

SEMG SIGNAL ANALYSIS

One major objective of the present investigation is to study the effect of muscle activities at different pressure points during different functional activities of arms. Here, in this present research work, two pressure points with four independent movements were selected for the surface electromyogram's study on upper arm muscles. Initially, the arm was kept at rest and the data was acquired without moving the hand. Then, EMG was acquired with hand closed with full tight force with elbow flexion. To study the EMG signal, it is required to be artifact-free.

4.1 POWER LINE ARTIFACT AND ITS REMOVAL

During surface electromyogram recording, main physiological signals *viz* motion artifacts due to cable movements can interfere with the recording. Additionally, power line signals of 50 Hz act as noise and produce significant artifacts. The electrode picks up this noise because the body acts as an antenna. It gets coupled to the amplifier used for amplifying the raw surface electromyogram signal. In relax state also, motion artifacts and power line interferences exist with surface electromyogram. Mains hum noise is the strongest artifact among all and can affect surface electromyogram significantly. Surface electromyogram being the voltage that is measured as a potential difference between two electrodes placed on the underlying muscle, both electrodes were expected to pick up the same power line artifact. This interference is a common mode noise and can be removed only when the impedance of the electrodes leading to active and reference inputs of the amplifier are in near vicinity, which in turn, demands identical contact impedance of electrodes attached to the skin. In addition to this, even after good contact of electrodes with skin, the electric power line interferences do not get eliminated because amplifiers are always ready to pick up the power line interference directly. A good shielding of circuitry is, therefore, desirable. In this study, power line noise was removed by applying 50 Hz elliptical notch filter. All the recorded signals were passed through the designed filter and the filtered signal is stored back.

4.2 SIGNAL CONDITIONING OF EMG

The softscope is initialized for the hardware setting to use data acquisition card. The trigger of soft scope was kept at continuous mode for fixed amount of time. After triggering, the waveform was stored in the workspace manually. The observations were taken three times from each subject. The samples were stored in the workspace with a specific name. The recorded surface electromyogram signals were passed through band pass filter with cut off frequencies 10 Hz and 500 Hz. Fast Fourier Transform (FFT) of the signal was obtained. The whole process of the recording and analysis is given in the flowchart shown in Figure 4.1.

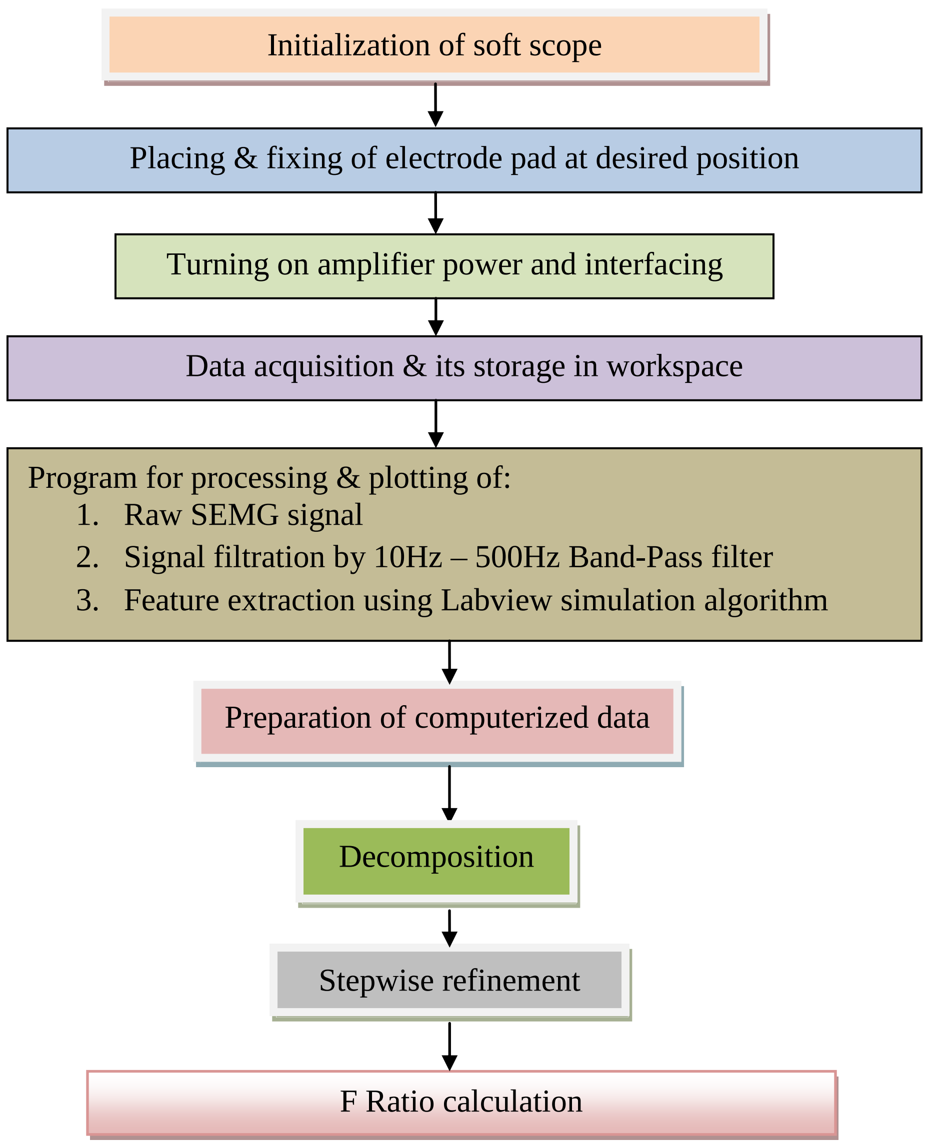


Fig. 4.1 Flow chart for the data acquisition, feature extraction and interpretation of signal

4.3 PARAMETERS EVALUATED FOR ANALYSIS

Specifically, Seven parameters were evaluated for the interpretation of surface electromyogram signal:

RMS value (Vrms): The root mean square (abbreviated RMS), also known as the quadratic mean, is a statistical measure of the magnitude of a varying quantity. It is especially useful when variants are both positive and negative. The RMS value of a set of values (or a continuous-timewaveform) is the square root of the arithmetic mean (average) of the squares of the original values (or the square of the function that defines the continuous waveform). Eq. (1) gives the RMS value for 'n' samples:

$$V_{rms} = \sqrt{\frac{(x_1^2+x_2^2+x_3^2+\ldots\ldots\ldots\ldots\ldots+x_n^2)}{n}} \qquad (1)$$

Standard deviation (SD): Standard Deviation shows the variation or dispersion from the average value. A low standard deviation indicates that the data points tend to be very close to the mean whereas high standard deviation indicates that the data are spread out over a large range of values. Standard deviation is given by the equation:

$$SD = \sqrt{\frac{\sum(x_i-u)^2}{n-1}} \qquad (2)$$

Power of signal (P): It computes the relationship between total electrical energy output of electromyogram signal and muscle contraction. One can measure the total power in band within the specified range based on the input signal.

Simple square integral (SSI) or Energy (EN): This is the summation of the square values of the amplitude of surface electromyogram signal samples. It is given by the equation:

$$E = \sum_{n=1}^{N} |\, x(n) \,|^2 \qquad (3)$$

Power spectral density (PSD): For a given signal, the power spectrum gives a plot of the portion of a signal's power falling within given frequency limits. The power spectrum of the periodic signal gives peaks at the fundamental harmonics. Quasi periodic signals give peaks at linear combinations of two or more irrationally related frequencies (often giving the appearance of a main sequence and sidebands) and chaotic dynamics gives broadband components of the spectrum, as depicted in Figure 4.5.

Mean absolute value (MAV): Since surface electromyogram is a complex signal in nature having noise, another parameter, mean absolute value, which gives the relation of amplitude rise to the variation in the frequency for different motions was calculated. It is defined by

$$\mathrm{MAV} = \frac{\sum_{1}^{N} |x(n)|}{N} \tag{4}$$

Sum of all values of power spectrum (PSUM): It computes the sum of all values of power spectrum for the given channel. It shows the strength of the variations as a function of frequency.

Programme were developed to plot the waveforms of raw filtered surface electromyogram signal, FFT plots and to calculate different parameters (Figure 4.2 to 4.4). Computerized stored data was analyzed using one way repeated factorial analysis of variance (ANOVA) technique. The data was firstly decomposed into four independent groups, and then the step by step data refinement for F ratio calculation was done for two different estimates i.e. variance of data between the group (SSB) and variance within the group (SSW). The last result of F ratio was computed from the processed and analyzed data stored in workspace.

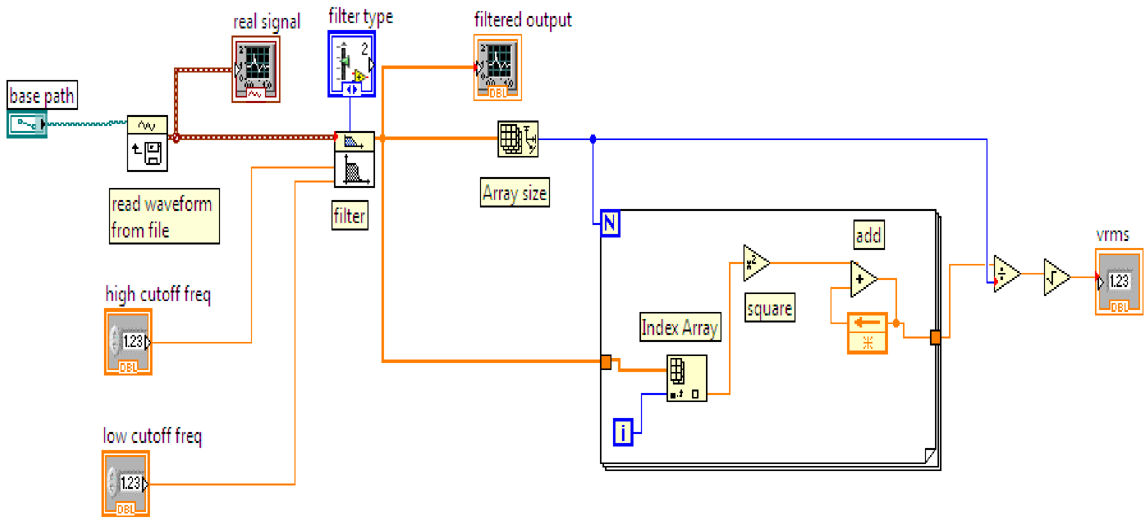


Fig. 4.2 Block diagram of program to calculate RMS value

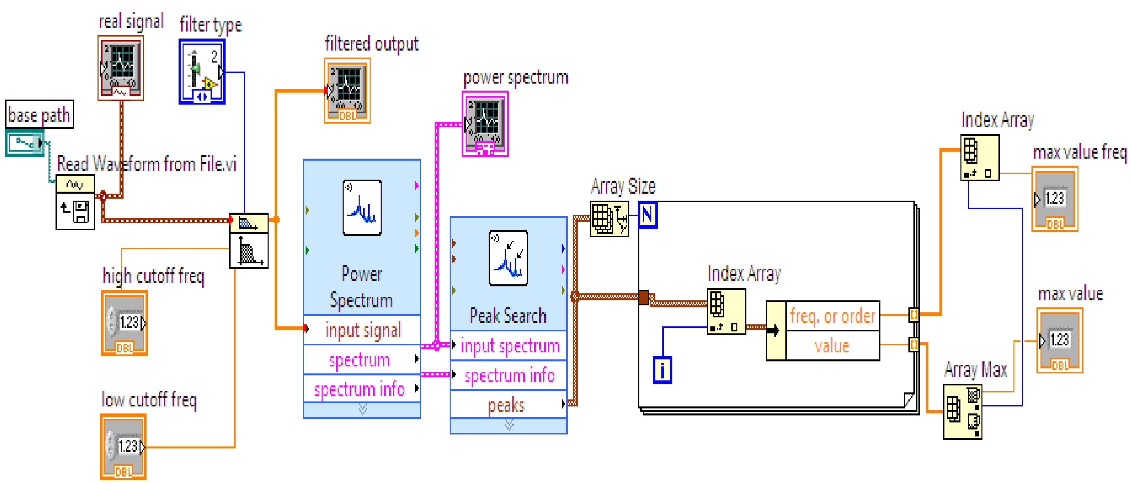


Fig. 4.3 Block diagram of program to calculate maximum frequency component

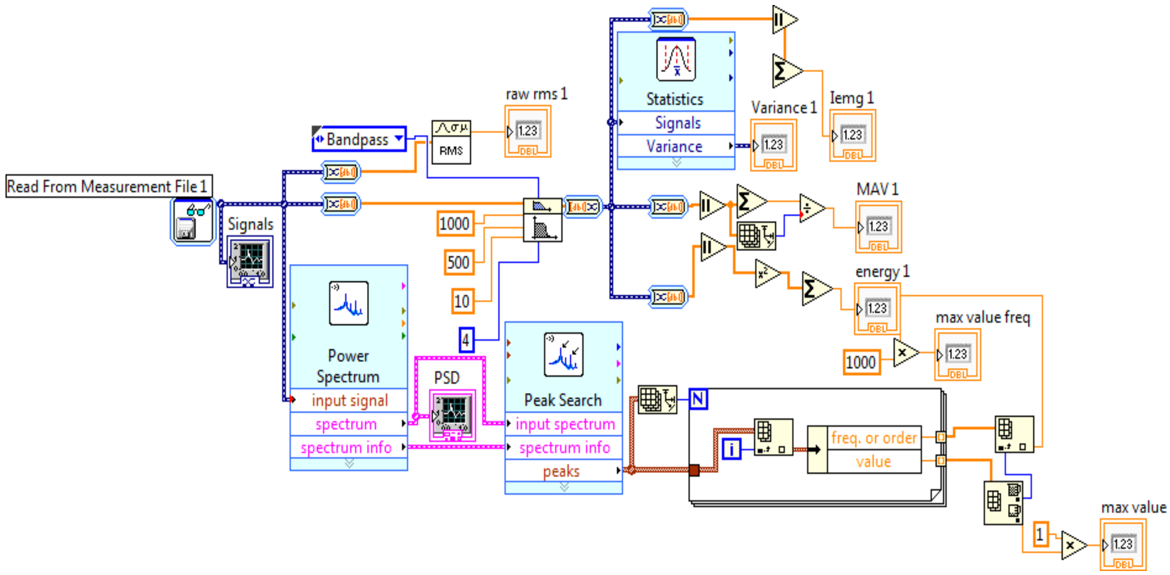


Fig. 4.4 A complete simulated program code for feature extraction

4.4 TEST RESULTS

Fig 4.5 shows the typical raw EMG signal and its power spectrum graphically. Table 4.1 shows the value of calculated parameters averaged on five subjects. Rise in RMS value and the power of the signal emphasize the presence of the signal’s strength. Fig 4.6 depicts the data graphically.

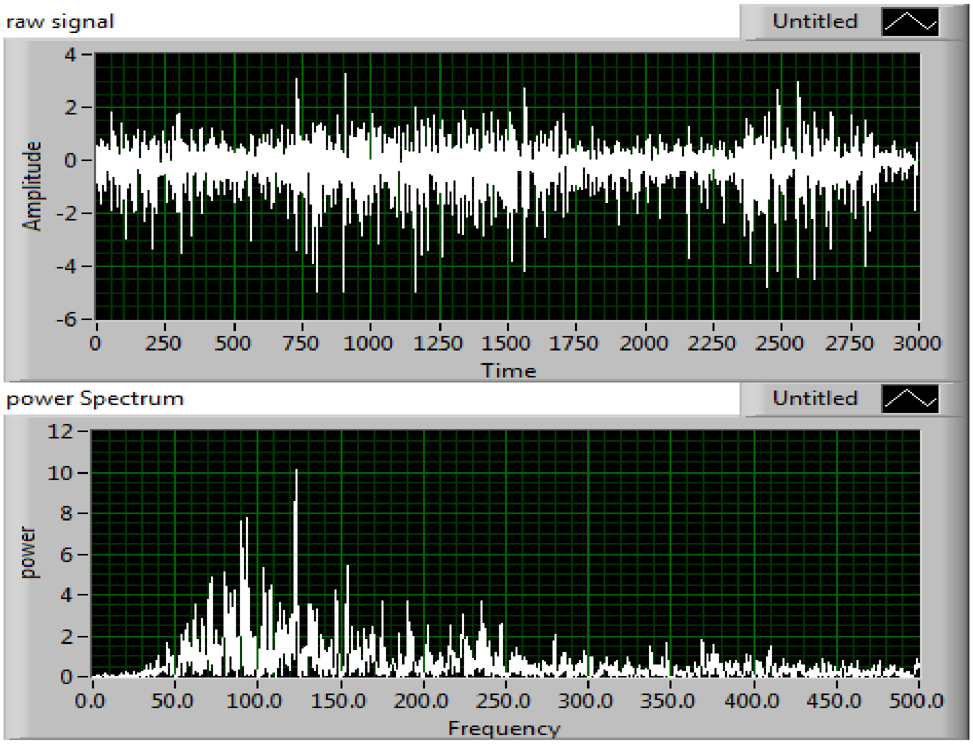


Fig. 4.5 Raw signal and power spectrum of Surface Electromyogram

Table 4.1 Average (all subjects) comparison of parameters

Parameters	Arm at rest	Arm with elbow flexion
VRMS	0.13	0.556
Standard Deviation	0.084	0.443
Power	0.050	0.877
Simple Square Integral	0.030	0.557
Mean absolute Value	0.070	0.289
Sum of all values of power spectrum	0.027	0.516

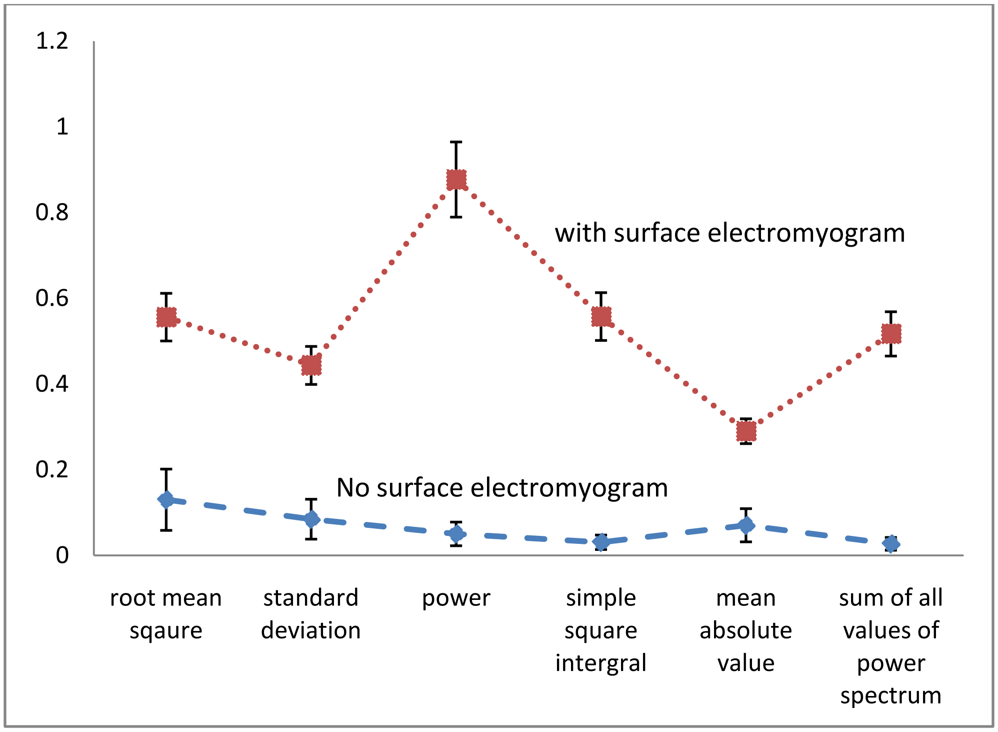


Fig. 4.6 The comparison of various evaluated parameters from sEMG for Arm at rest and arm with elbow flexion

Table 4.1 clearly indicates substantial difference in values between two groups. Although all extracted features have specific advantages, however, the most commonly used technique for analyzing the power of the signal is the root mean square (RMS) value. The root mean square (RMS) values were computed for each signal and force data file, as RMS is the parameter that more completely reflects the physiological correlates of the motor unit behavior during a muscle contraction. From Figure 4.7, V_{RMS} result (average of 5 subjects) shows an indicative rise for different arm movements and depicts the proportionality with the force of contraction of the muscles.

Further the Euclidean Distance (ED) has been evaluated between two groups as a separation index because of its simplicity of computation. It is calculated as the root of square differences between coordinates of a pair of objects. The ED (1,2) is defined as:

$$ED\ (1,2) = \sqrt{(p1- p2)^2 + (q1- q2)^2} \quad (5)$$

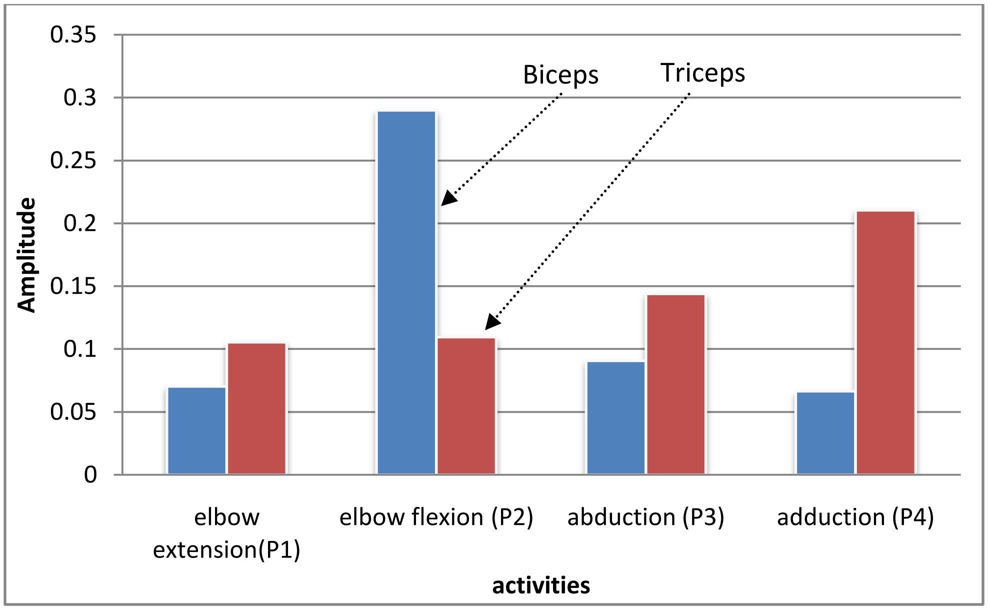


Fig. 4.7 V_{RMS} results for different arm movements

Since previous work suggested [*Phinyomark et al., 2013*] [*Alemu et al., 2003*] [*Subasi, 2012*] [*Nakamura, 2004*] [*Nawab et al., 2010*] [*Stashuk, 2001*] [*Enoka, 2010*] [*Phinyomark et al., 2012*] [*Phinyomark et al., 2009*] [*Farina et al., 2000*] [*Boostani et al., 2003*] that the highest quality of surface electromyogram depends upon maximum class separability, robustness, and complexity features., so in this investigation, maximum class separability was evaluated by root mean square and mutual separation index, as root mean square is the statistical measure of the magnitude of a varying quantity and is especially useful when variants are positive and negative; while mutual separation index helps to investigate the distance between two different separate groups and the variation among features can be easily addressed. Mutual Separation Index (MSI) is give in Table 4.2. These mutual separation index values were used to analyze the elbow extension, flexion, abduction and adduction arm movements to study the effect of two muscle locations on each other.

Different extracted features helped in establishing the relationship for surface electromyogram signal corresponding to independent voluntary muscular contractions. Independent results for all participating subjects are as tabulated from Table 4.3 to Table 4.7 for Biceps muscle and from Table 4.8 to Table 4.12 for Triceps muscle respectively. Their average results are tabulated in Table 4.13 for Biceps and in Table 4.14 for Triceps muscle.

Table 4.2 Mutual separation index for two groups with different movements

Movement type	Euclidean distance	Mutual Separation Index (Average of 5 subjects)
Elbow extension	0.034	0.266
Elbow flexion	0.361	0.635
abduction	0.115	0.313
adduction	0.264	0.617

Table 4.3 Comparison of extracted features on biceps muscle of subject 1

Extracted Features	elbow extension	elbow flexion	abduction	adduction
V_{RMS}	0.08	0.59	0.19	0.14
Standard Deviation	0.0438	0.4428	0.1376	0.0777
Power	1.168	106.4	6.79	3.214
simple square integral	12.748	137.151	86.55	12.74
Mean absolute Value	0.0495	0.1593	0.1243	0.0495
Total sum of all values of spectrum	0.0086	0.6075	0.0551	0.0276

Table 4.4 Comparison of extracted features on biceps muscle of subject 2

Extracted Features	elbow extension	elbow flexion	abduction	adduction
V_{RMS}	0.12	0.42	0.12	0.07

Standard Deviation	0.0762	0.3388	0.0842	0.0382
Power	3.115	45.65	2.78	1.025
simple square integral	17.413	344.633	21.26	4.386
Mean absolute Value	0.0592	0.2423	0.0641	0.0296
Total sum of all values of spectrum	0.0191	0.3167	0.0206	0.0069

Table 4.5 Comparison of extracted features on biceps muscle of subject 3

Extracted Features	elbow extension	elbow flexion	abduction	adduction
V_{RMS}	0.10	0.77	0.14	0.12
Standard Deviation	0.0515	0.6446	0.0784	0.0706
Power	1.507	153.4	3.648	2.37
simple square integral	7.999	1244.8	18.359	14.944
Mean absolute Value	0.0397	0.4642	0.0603	0.0554
Total sum of all values of spectrum	0.0146	0.9776	0.0287	0.0193

Table 4.6 Comparison of extracted features on biceps muscle of subject 4

Extracted Features	elbow extension	elbow flexion	abduction	adduction

V_{RMS}	0.14	0.47	0.20	0.19
Standard Deviation	0.1028	0.4143	0.1366	0.1442
Power	5.59	42.09	6.39	6.990
simple square integral	49.032	513.99	56.069	62.298
Mean absolute Value	0.0900	0.2962	0.1066	0.1088
Total sum of all values of spectrum	0.0316	0.2570	0.0488	0.0516

Table 4.7 Comparison of extracted features on biceps muscle of subject 5

Extracted Features	elbow extension	elbow flexion	abduction	adduction
V_{RMS}	0.21	0.53	0.18	0.17
Standard Deviation	0.1487	0.3765	0.1285	0.1177
Power	13.74	91.00	10.23	9.08
simple square integral	66.407	546.349	63.731	49.032
Mean absolute Value	0.1137	0.2873	0.0987	0.0900
Total sum of all values of spectrum	0.0615	0.4261	0.0499	0.0422

Table 4.8 Comparison of extracted features on triceps muscle of subject 1

Extracted Features	elbow extension	elbow flexion	abduction	adduction
V_{RMS}	0.11	0.16	0.32	0.54
Standard Deviation	0.0530	0.0971	0.2113	0.3750
Power	1.901	6.40	21.86	66.56
simple square integral	8.42	28.21	133.98	420.599
Mean absolute Value	0.0416	0.0763	0.1559	0.2877
Total sum of all values of spectrum	0.0186	0.0388	0.1477	0.2912

Table 4.9 Comparison of extracted features on triceps muscle of subject 2

Extracted Features	elbow extension	elbow flexion	abduction	adduction
V_{RMS}	0.10	0.11	0.20	0.29
Standard Deviation	0.0546	0.0684	0.1250	0.1771
Power	1.717	2.72	8.330	15.05
simple square integral	8.936	14.028	46.80	93.717
Mean absolute Value	0.0430	0.0530	0.0979	0.1374
Total sum of all values of spectrum	0.0131	0.0190	0.0597	0.1222

Table 4.10 Comparison of extracted features on triceps muscle of subject 3

Extracted Features	elbow extension	elbow flexion	abduction	adduction
V_{RMS}	0.05	0.09	0.13	0.34
Standard Deviation	0.0253	0.0667	0.0808	0.2143
Power	4.16	2.12	4.391	24.55
simple square integral	1.934	13.348	19.52	138.04
Mean absolute Value	0.0197	0.0523	0.0622	0.1576
Total sum of all values of spectrum	0.0037	0.0147	0.0269	0.1411

Table 4.11 Comparison of extracted features on triceps muscle of subject 4

Extracted Features	elbow extension	elbow flexion	abduction	adduction
V_{RMS}	0.19	0.27	0.31	0.31
Standard Deviation	0.1316	0.1977	0.2418	0.2435
Power	11.21	21.23	17.36	18.65
simple square integral	117.22	117.13	117.617	175.517
Mean absolute Value	0.2882	0.1533	0.1813	0.1819
Total sum of all values of spectrum	0.0561	0.1107	0.1312	0.1418

Table 4.12 Comparison of extracted features on triceps muscle of subject 5

Extracted Features	elbow extension	elbow flexion	abduction	adduction
V_{RMS}	0.25	0.40	0.37	0.53
Standard Deviation	0.1773	0.2817	0.3034	0.3824
Power	23.05	58.40	30.34	91.26
simple square integral	100.404	259.342	300.714	517.22
Mean absolute Value	0.1354	0.2128	0.2223	0.2882
Total sum of all values of spectrum	0.0988	0.2674	0.2817	0.4194

Table 4.13 Average (all subjects) comparison of extracted features on biceps muscle

Extracted Features	elbow extension	elbow flexion	abduction	adduction
V_{RMS}	0.13	0.556	0.166	0.138
Standard Deviation	0.08	0.443	0.113	0.089
Power	5.024	87.708	5.967	4.535
simple square integral	30.7198	557.384	49.193	28.68
Mean absolute Value	0.070	0.289	0.090	0.066
Total sum of all values of spectrum	0.027	0.516	0.040	0.029

Table 4.14 Average (all subjects) comparison of extracted features on triceps muscle

Extracted Features	elbow extension	elbow flexion	abduction	adduction
V_{RMS}	0.14	0.206	0.226	0.402
Standard Deviation	0.088	0.142	0.192	0.278
Power	8.407	18.174	16.456	43.214
simple square integral	27.382	86.411	123.726	269.018
Mean absolute Value	0.105	0.109	0.143	0.210
Total sum of all values of spectrum	0.038	0.090	0.129	0.222

To further extend the study of relational interpretations of selected operations on the chosen locations on upper arm, two analytical approaches were applied: Firstly, with one operation, the effect on surface electromyogram signal is seen at chosen locations. Secondly, at one location, the effect on surface electromyogram signal is studied for chosen operations. Table 4.15 was formulated after detailed experimental analysis, which gives maximum or minimum surface electromyogram signal for a specific operation. Table 4.16 was formulated which helps in identifying arm motion on upper arm for multiple electrode locations. From the results, one can conclude the linear relationship between surface electromyogram signal and muscular force.

Table 4.15 Prominent locations on above-elbow arm for different motions

Motions	Surface electromyogram signal quality	
	Biceps movement	Triceps movement

elbow extension (P1)	Low	low
elbow flexion (P2)	high	moderate
Abduction (P3)	medium	medium
Adduction (P4)	moderate	high

Table 4.16 Prominent positions on above-elbow arm for different movements

Description	elbow extension (P1)	elbow flexion (P2)	Abduction (P3)	Adduction (P4)
Max. dominant movement/position	---	biceps (0.556)	---	triceps (0.402)
Min. dominant movement/ position	biceps/triceps (0.13/0.14)	---	---	---
Moderate movement/ position	---	---	biceps/triceps (0.166/0.226)	---

4.5 STATISTICAL ANALYSIS

The electrical activity of a muscles measured by surface electromyogram exhibits complex behavior with nonlinear dynamic properties. This behavior takes the form of surface electromyogram patterns with different complexities. Considering this fact, the statistical theory may be a better approach than traditional linear methods in characterizing the intrinsic nature of surface electromyogram. The study of the characterization can contribute to the understanding of the surface electromyogram dynamics and underlying muscles processes and search for its physiological significance. Surface electromyogram patterns at the locations for the three different cases of grip were considered for the statistical analysis. The data samples were recorded and processed by program and then exported to MS-EXCEL where the in-built statistical functions were used for comparison.

To further extend the study of relational interpretations of selected operations on the arm, two analytical approaches were applied- first, the effect on the surface electromyogram signal at chosen location and the second, the effect for chosen motion. For first case, principal component analysis (PCA) was used to explain variance structure of a set of variables as a dimensionality - reduction technique for correlated variables for the interpretation of arm movements.

4.5.1 Results Using Principal Component Analysis

In the analysis, Principal Component Analysis (PCA) was carried out in terms of the percentage of variance since it is a traditional multivariate statistical method commonly used to reduce the number of predictive variables and solve the multi colinearity problem, which maximizes the variance of the original data set. Table 4.17 displays the total variance explained at four stages, showing the factors and their associated Eigen values, the percentage of variance and the cumulative percentage.

Table 4.17 Total Variance

Com ponent	Initial Eigen values			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	7.406	92.57	92.579	7.406	92.57	92.579	3.003	37.541	37.541
2	0.314	3.919	96.498	0.314	3.919	96.498	2.520	31.496	69.037
3	0.197	2.463	98.962	0.197	2.463	98.962	2.389	29.866	98.902
4	0.053	0.663	99.625	0.053	0.663	99.625	0.058	0.723	99.625
5	0.014	0.172	99.797	---	---	---	---	---	---
6	0.011	0.138	99.935	---	---	---	---	---	---
7	0.005	0.056	99.991	---	---	---	---	---	---
8	0.001	0.009	100.00	---	---	---	---	---	---

If all four factors were extracted, then 99 percent of variance would be explained. In this case, there was one factor with Eigen values greater than 1. The “% of variance” column tells how much of the total variability (in all of the variables together) can be accounted for by each of these summary scales or factors. Factor 1 accounts for 37.541 of the variability among all eight variables. For this variance component, its Eigen value, which is an index of strength of the factor, is 7.406, so the value of variance is 0.925 accounted for as any single variable. The fourth component explains 99.625 of the total variance in the variables which are included on the components. Here it is noted that first few factors explain relatively large amount of variance, whereas subsequent factors explain only small variance. Before rotation, factor 1 accounted for more variance than remaining three, i.e. 92.579 compared to 3.919, 2.463, and 0.663. However, after rotation it accounts a variance of 37.541 compared to 31.496, 29.866 and 0.723.

The Kaiser-Meyer Olkin (KMO) statistics varies between 0 and 1, where a value 0 indicates that the sum of partial correlations diffused means analysis is inappropriate and value close to 1 indicates patterns of correlations compact so analysis yield distinct and reliable factor, here this value is 0.743. A value greater than 0.5 is acceptable [*Field, 2005*] so one can easily come to result that the Barlett test is significant and the Kaiser-Meyer Olkin measure of sampling adequacy is far greater than acceptable level, so giving significant recorded data result (i.e. *0.743*).

4.5.2 Results Using ANOVA

To further extend the study of relational interpretations of selected operations on the arm, statistical technique of Repeated Factorial Analysis of Variance on experimental data was implemented for the interpretation of signal's class separability in order to identify the best surface electromyogram signal amplitude for different voluntary contractions to establish the better myoelectric signal-force relationship.

The technique of analysis of variance is to test for differences among the means of the populations by examining the amount of variations within each of these samples. Under the one way analysis of variance, we consider only one factor and then observe that several possible types of samples can occur within that factor. The technique implemented for determining if there are differences within that factor involves the following steps:

(1) Obtain the mean of each sample as:

$$\bar{A}_1, \bar{A}_2, \bar{A}_3 \ldots\ldots\ldots\ldots\ldots\ldots \bar{A}_k \text{ where there are k samples} \quad (5)$$

(2) Find out the mean of samples means as follows:

$$\tilde{\bar{A}} = \frac{\bar{A}1 + \bar{A}2 + \bar{A}3 \ldots\ldots\ldots\ldots + \bar{A}k}{\text{No.of samples (k)}} \quad (6)$$

(3) Take the deviation of the samples means from the means of the sample means and calculate the square of such deviations which may be multiplied by the number of items in the corresponding sample and then obtain their total, which is called sum of square for variance between the samples (SSB):

$$SSB = n_1 (\bar{A}_1 - \tilde{\bar{A}})^2 + n_2 (\bar{A}_2 - \tilde{\bar{A}})^2 + \ldots\ldots\ldots\ldots + n_k (\bar{A}_1 - \tilde{\bar{A}})^2 \quad (7)$$

(4) Divide the result of step (7) by the degree of freedom between the samples to obtain variance or mean square between (MSB) samples:

$$MSB = \frac{SSB}{(k-1)}, \quad \text{(k-1) is degree of freedom between samples} \quad (8)$$

(5) Obtain the deviations of the values of the sample items for all samples from the corresponding means of the samples and calculate the square of deviations and obtain their total and is called sum of square for variance within the samples (SSW):

$$SSW = \sum (\bar{A}_{1i} - \tilde{\bar{A}})^2 + \sum (\bar{A}_{2i} - \tilde{\bar{A}})^2 + \ldots\ldots\ldots\ldots + \sum (\bar{A}_{1i} - \tilde{\bar{A}})^2, \ i = 1, 2, 3\ldots \quad (9)$$

(6) Divide the result of step (9) by the degree of freedom within the samples to obtain variance or mean square within (MSW) samples:

$$MSW = \frac{SSW}{(n-k)} \quad (10)$$

Where (n-k) represents degree of freedom within samples

(7) Then sum of squares of deviations for total variance is calculated by adding the squares of deviations taken from the means of the sample means:

$$SST = \sum (\bar{A}_{ij} - \tilde{\bar{A}})^2, \text{ where } \quad i = 1, 2, 3\ldots \text{ and, } j = 1, 2, 3\ldots\ldots\ldots\ldots \quad (11)$$

This total should be equal to the total of the results of the (7) and (9) steps i.e.

$$SST = SSB + SSW \tag{12}$$

And degree of freedom for between and within must add up to the degree of freedom for total variance:

$$(n\text{-}1) = (k\text{-}1) + (n\text{-}k) \tag{13}$$

(8) Finally, F- ratio may be calculated as:

$$\text{F ratio} = \frac{\text{MSB}}{\text{MSW}} \tag{14}$$

This ratio is used to investigate whether the difference among several sample means is significant with respect to the variability within each sample or just matter of sampling fluctuations. This ratio is compared against F value for the given degree of freedom at different levels of significance. Higher the calculated value of F- ratio above the table value, greater is the likelihood that the population means are not all equal [*Coakers, 2005*] the more definite and significant is the data and differences between the means are due to real effects..

In order to compare the means of the four independent variable groups (G1 – G4) and to decide about the effectiveness of the surface electromyogram signal for different motions, a one way and two way analysis of variance (ANOVA) has been implemented respectively. The one way analysis of variance with four groups for Biceps and Triceps motions is shown in Table 4.18 and Table 4.19 while the result for two way analysis of variance with defined groups for Biceps and Triceps motions is as shown in Table 4.20 and Table 4.21.

Table 4.18 One way analysis of variance result for biceps motion

Source of variation	**Sum of Square (SS)**	**Degree of freedom (dof)**	**Mean Square (MS)**	**F Ratio (F)**	**Level of significance (p value)**	**Critical value (Fc)**
Sum of square between group	0.638	3	0.212	**35.11**	**0.0001**	3.23
Sum of square	0.096	16	0.006	---	---	---

within/group						
Total sum of square	0.734	19	---	---	---	---

Table 4.19 One way analysis of variance result for triceps motion

Source of variation	**Sum of Square (SS)**	**Degree of freedom (dof)**	**Mean Square (MS)**	**F Ratio (F)**	**Level of significance (p value)**	**Critical value (Fc)**
Sum of square between group	0.186	3	0.062	**5.22**	**0.0001**	3.23
Sum of square within/group	0.195	16	0.011	---	---	---
Total sum of square	0.377	19	---	---	---	---

Table 4.20 Two way analysis of variance results for biceps motions

Source of variation	**Sum of Square (SS)**	**Degree of freedom (dof)**	**Mean Square (MS)**	**F Ratio (F)**	**Level of significance (p value)**	**Critical value (Fc)**
Sum of square between group	0.638	3	0.212	**35.16**	**0.00003**	3.49
Sum of square within group	0.024	4	0.006	---	---	---
Error	0.072	12	0.006	---	---	---
Total sum of square	0.734	19	---	---	---	---

Table 4.21 Two way analysis of variance results for triceps motions

Source of variation	Sum of Square (SS)	Degree of freedom (dof)	Mean Square (MS)	F Ratio (F)	Level of significance (p value)	Critical value (Fc)
Sum of square between group	0.216	3	0.072	**12.96**	**0.0004**	3.49
Sum of square within group	0.138	4	0.034	---	---	---
Error	0.066	12	0.005	---	---	---
Total sum of square	0.421	19	---	---	---	---

Note: Rejection of the null hypothesis takes place when $p < 0.05$ i.e. when $F < Fc$.

The experimental recorded data was divided into four broad groups with respect to upper arm motion level's (elbow extension; elbow flexion; abduction and adduction respectively). One way and two-way analysis of variance was performed for all four ranges of upper arm motions. Here, in these cases, the p value < 0.05, and F > Fc, so the hypothesis that no difference exists in the percentage of event detection due to different arm motions can be rejected meaning that their interaction have significant factor contributing to the response "arm motion event detection".

It was observed that there was a significant difference in amplitude gain across different motions as $F(3, 16) = 35.11, 35.16$, $p < 0.05$ and $F(3, 16) = 5.223, 12.96$, $p < 0.05$ for two independent muscles for one and two way analysis of variance. From Tables 4.18 - Table 4.21, the F ratio is greater than critical value (Fc) and means are significantly different so it is concluded that there is significant difference between the groups (SSB) than within groups (SSW). The p-values for biceps $F(3, 16)$ and triceps $F(3, 16)$ for both way of analysis of variance were found to be 0.0001, 0.0001, 0.0003 and 0.0004 respectively which is < 0.05 so the null hypotheses of equal means was rejected and finally, it was concluded that the test statistic was significant at this level.

5

SEMG SIGNAL CLASSIFICATION

Next aim of this work is to extract signal information from the recorded signals for class separability of upper arm motions. This can only be achieved by extracting accurate patterns of EMG signal corresponding to different arm motions after the EMG signal is denoised. In this chapter, a comparative study to evaluate the wavelet denoising for optimal motor unit action potential detection through the decomposition based on different wavelet functions of Daubechies, Coiflet and Symmlets families has been carried out and results are tabulated. Thereafter, Linear Discriminant Analysis and Artificial Neural Network pattern classifier approaches are described to analyze classification performance for different upper arm movements.

5.1 DENOISING THE sEMG SIGNAL

The capability of Wavelet Transform for denoising purposes prior to pattern classification is well known. Wavelet de-noising can be divided into the following steps:

- Make multi-scale decomposition of the raw signals
- Estimate the noise, choose and apply the threshold analysis, and
- Reconstruct the surface electromyogram signals by the revised wavelet coefficients

Figure 5.1 shows the step wise procedure of wavelet denoising which is able to generate noise free surface electromyogram signal.

5.1.1 Wavelet Decomposition

The ability of the Wavelet Transform to extract features from the signal is dependent on the appropriate choice of the mother wavelet function. Even though there is no well-defined rule for selecting a wavelet basis function in a particular application or analysis, some properties of the wavelets make a specific mother wavelet more suitable for a given application and signal type [*Phinyomark et al., 2010*].

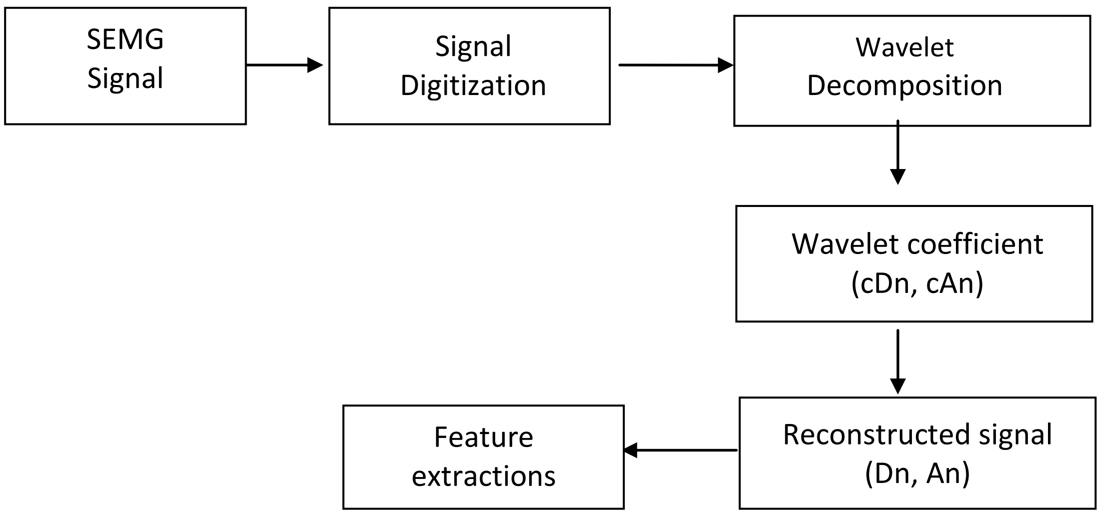


Fig. 5.1 Wavelet denoising procedure

The first step of wavelet denoising procedure is selection of wavelet function or mother wavelet. The right wavelet function ensures perfect reconstruction and performs better analysis. Next step is the selection of the number of decomposition levels of signal.The DWT of a signal s[n] is calculated by passing it through a series of filters (Figure 5.2). First, the signal s[n] ispassed through a low-pass filter with impulse response g[n], resulting in a convolution y[n] of the two. The signal also goes simultaneously through a high-pass filter with impulse response h[n]. The outputs give the detail coefficients (from the high-pass filter, z_{high}[n]) and the approximation coefficients (fromthe low-pass filter, z_{low}[n]). The filter outputs are then down-sampled as given by equation 1 &2.

$$Z_{low}[n] = \sum_{k=-\infty}^{\infty} x[k].\,g[2n - k] \qquad (1)$$

$$Z_{high}[n] = \sum_{k=-\infty}^{\infty} x[k].\,g[2n - k] \qquad (2)$$

Previous research shows [*Phinyomark et al., 2012*] [*Hussain et al., 2009*] that the decomposition levels that are suitable for surface electromyogram signals are four. Accordingly, fourth level of decomposition was considered.

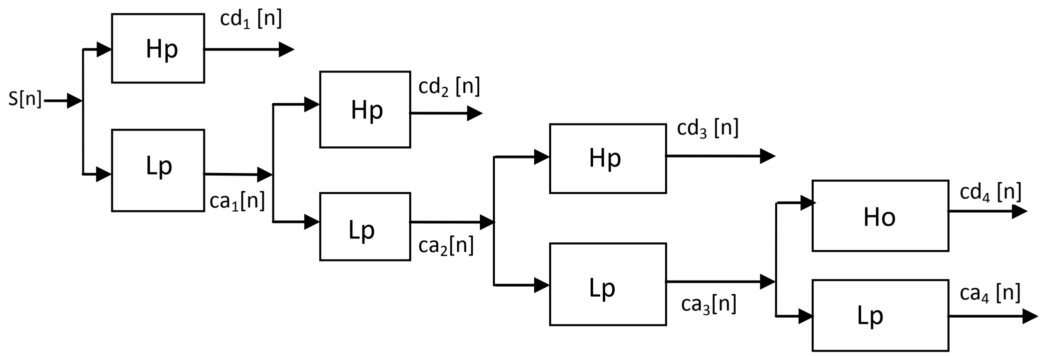


Fig. 5.2 Four levels of wavelet decomposition tree

According to Figure 5.2, the raw electromyogram signal s[n] is decomposed by the discrete wavelet transform (DWT) to obtain the detail (cD) and approximation coefficients (cA). The cDs contain high frequency components from the high-pass filter (Ho) and cAs contain low frequency components from the low-pass filter (Lo). For wavelet signal denoising, noise parts usually fall in the cD bands. After the four levels of WT decomposition, cD1 [n], cD2 [n], cD3 [n] and cD4 [n] detail coefficients and cA4 [n] approximation coefficients were the available coefficients of the transform.

5.1.2 Thresholding

After decomposition, the threshold value (THR) is fixed based on the noise variance and is applied to the cds using only a linear or non-linear transform.

5.1.3 Wavelet Reconstruction

Finally, the denoised surface electromyogram signal is reconstructed based on the modified detail (Ds) and the retained approximation (As) coefficients [*Phinyomark et al., 2011*]. An inverse transform is performed on the coefficients after threshold, providing a good approximation of the surface electromyogram signal. The reconstruction is the reverse process of wavelet decomposition. The approximation (A4[n]) and detail coefficients (D1[n], D2[n], D3[n], D4[n]) at every level are up-sampledby two, passed through the low-pass and high-pass synthesis filters and then added. This process is continued through the same number of levels as in the decomposition process to obtain the original surface electromyogram signal.

In this study, four levels of wavelet decomposition/reconstruction were applied. Figure 5.3 gives the four levels of wavelet reconstruction. According to Figure 5.3, the approximation coefficient A4[n] and detail coefficient D4 [n] are passed through the low-pass and high-pass filters and then added toget A3 [n], A3 [n] and D3 [n] are added to get A2 [n] and the process continues until the denoised surface electromyogram signal s[n] is achieved.

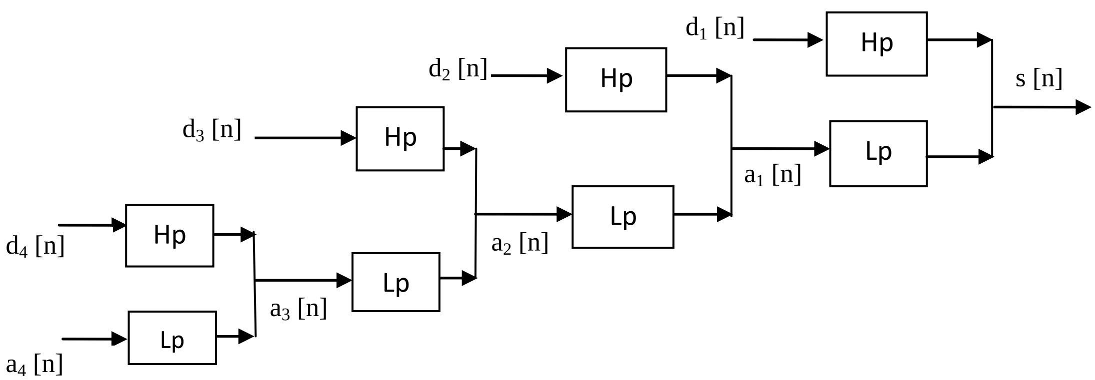


Fig. 5.3 Four levels of wavelet reconstruction tree

To investigate the behavior of muscle fibers during voluntary motions of Elbow extension (ee), Elbow flexion (ef), Abduction (abd) and Adduction (add), wavelet denoising by different order Daubechies, Coiflet and Symmlets wavelets was done. Denoised classification results for different wavelet families in terms of amplitude estimation are presented in Table 5.1 to Table 5.6, where average root mean squares of the class separability for different types of upper arm motions for biceps and triceps muscle locations are tabulated.

Table 5.1 Average denoised RMS value of Daubechies wavelet for biceps muscle

Order	ee	ef	abd	add	average
db2	0.07	0.370	0.076	0.076	**0.148**
db4	0.07	0.364	0.07	0.076	0.145
db6	0.064	0.352	0.074	0.072	0.140
db8	0.062	0.338	0.07	0.074	0.136
db10	0.062	0.326	0.072	0.07	0.132
db12	0.06	0.322	0.072	0.068	0.131
db14	0.062	0.320	0.07	0.068	0.130

Table 5.2 Average denoised RMS value of Coiflet wavelet for biceps muscle

Order	ee	ef	abd	add	average
coif1	0.06	0.284	0.062	0.064	**0.117**
coif3	0.058	0.264	0.060	0.064	0.111
coif5	0.06	0.260	0.056	0.060	0.109

Table 5.3 Average denoised RMS value of Symmlets wavelet for biceps muscle

Order	ee	ef	abd	add	average
sym2	0.064	0.290	0.060	0.064	**0.119**
sym4	0.060	0.272	0.058	0.062	0.113
sym6	0.058	0.274	0.058	0.062	0.113
sym8	0.058	0.278	0.058	0.062	0.114

Table 5.4 Average denoised RMS value of Daubechies wavelet for Triceps muscle

Order	ee	ef	abd	add	average
db2	0.084	0.10	0.136	0.172	**0.123**
db4	0.082	0.098	0.130	0.150	0.115
db6	0.068	0.084	0.122	0.142	0.104
db8	0.07	0.086	0.126	0.138	0.105
db10	0.07	0.080	0.126	0.134	0.102
db12	0.068	0.078	0.122	0.124	0.098
db14	0.068	0.078	0.116	0.122	0.096

Table 5.5 Average denoised RMS value of Coiflet wavelet for Triceps muscle

Order	ee	ef	abd	add	average
coif1	0.078	0.09	0.112	0.160	**0.110**
coif3	0.074	0.082	0.104	0.144	0.101
coif5	0.074	0.084	0.102	0.142	0.100

Table 5.6 Average denoised RMS value of Symmlets wavelet for Triceps muscle

Order	ee	ef	abd	add	average
sym2	0.076	0.09	0.108	0.160	**0.108**
sym4	0.070	0.086	0.112	0.150	0.104
sym6	0.070	0.084	0.106	0.146	0.101
sym8	0.070	0.06	0.108	0.144	0.095

From Table 5.1, the recruitment of muscle fibers during voluntary contractions in terms of denoised amplitude estimation based best average class separability result for Biceps muscle with independent four groups is for db2. Next, from Table 5.2, the best average class separability result for Biceps muscle with independent four groups is for coif1and finally, from Table 5.3, the best average class separability result for Biceps muscle with independent four groups is for symlet2 wavelet among all tabulated wavelet families. Similarly, from Table 5.4 – Table 5.6, it can be inferred that the denoised amplitude estimation based best average class separability result for Triceps muscle with independent four groups are for db2, coif1 and symlet2 wavelet among all tabulated wavelet families respectively.

5.2 Linear Discriminant Analysis

The purpose of discriminant function analysis is to understand the data set that results from the procedure and can give insight into the relationship between group membership and the variable used (Power of signal) to predict group membership.It has been used to investigate independent variable mean differences between groups formed by the dependent variable and also to determine the percent of variance in the dependent variable explained by the independents over and above the variance accounted for by control variables.

In this method, a Wilks' lambda is used to test if the discriminant model as a whole is significant or not. It is the ratio of within-groups sums of squares to the total sums of squares. This is the proportion of the total variance in the discriminant scores not explained by differences among groups and secondly, if the F test shows significance, then the individual independent variable is assessed to see which one differs significantly in mean by group and these are used to classify the dependent variable. Lambda varies from 0 to 1, with 0 meaning group means differ and 1 meaning all group means are the same. The associated significance value indicates whether the difference is significant. Here, the Wilks Lambda of 0.545 has a significant value (Sig. = 0,000); thus, the group means appear to differ. The associated chi-square statistic (22.744) tests the hypothesis that the means of the functions listed are equal across groups. The small significance value (p-value) indicates that the discriminant function does better than chance at separating the groups. Since the value of $p < 0.05$, so it was concluded that the model is a good fit for the significance of data.

As we are interested in the relationship between a group of independent variables and one categorical variable, so it would be beneficial to know how many dimensions one would need to express this relationship. Using this relationship, one can predict a classification based on the independent variables or assess how well the independent variables separate the categories in the classification. Larger the Eigen value (0.834 in this study), the more of the variance in the dependent variable is explained by that function. The canonical correlation (0.674) is the measure of association between the discriminant function and the dependent variable. The square of canonical correlation coefficient is the percentage of variance explained in the dependent variable. Finally, the classification table also called prediction matrix or table used to assess the performance of model is shown in Table 5.7 as it helps in describing simple summary of number and percent of subjects classified correctly and incorrectly.

a. 85.0% of original grouped cases correctly classified.
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
c. 85.0% of cross-validated grouped cases correctly classified.

Table 5.7 Classification Result (a, c)

		Pass	**Predicted Group Membership**		**Total**
			0.00	1.00	
original	count	0.00	29	1	30
		1.00	5	5	10
	%	0.00	96.7	3.3	100.0
		1.00	50.0	50.0	100.0
Cross-validated	count	0.00	29	1	30
		1.00	5	5	10
	%	0.00	96.7	3.3	100.0
		1.00	50.0	50.0	100.0

Table 5.7 shown above also gives information about *actual* group membership vs. *predicted* group membership. So it is concluded that overall percentage of correct classification is 85.0%

Looking at the columns in the Table 5.7 instead of the rows, one can also calculate Positive and Negative probability value:

a. Positive Probability Value gives the confidence in predicted results. Higher probability means that there is high chance that a predicted model will actually be a significant model = 85.29%.
b. Negative Probability Value is similar to sensitivity = 83.33%.
c. The specificity is the percentage of correct classification predicted in model = 96.70%.
d. The sensitivity is the percentage of model correctly predicted = 50.00%.

Finally, the average classification result calculated for db2, coif1 and sym2 Wavelet family after applying Linear Discriminating Analysis are 85.00%, 82.50% and 80.00% respectively, whereas among different best classification results the better classifier is db2 Wavelet where 85.0% of original grouped cases are correctly classified.

5.3 ARTIFICIAL NEURAL NETWORK CLASSIFIER

The Artificial Neural Network model with six parameters i.e. Root mean square value, Energy of signal, Variance, Simple square integral, Power and Integrated electromyogram as inputs and only two target outputs i.e. 'LOW' and 'HIGH' surface electromyogram state was realized.

The first five extracted features help in characterizing different upper arm movements, while sixth parameter integrated electromyogram is an alternative view of surface electromyogram signal that clearly helps in findings the patterns of muscle activity. Integrated Electromyogram averages out noise spikes in the raw data to provide more accurate indication of the output level since it calculates moving average of the data by first rectifying each point in the sample range and then computing the mean. It, thus, helps in segregating the number of active underlying muscle and motor nerve fibers for better reflecting skeletal muscle tonus being reflected by basal level of electrical activity associated with the corresponding movements. The comparison result of these parameters simultaneously analyzed from Biceps and Triceps muscles after being averaged for ten subjects are tabulated in Table 5.8 and Table 5.9.

Table 5.8 Comparison of extracted parameters for biceps muscle

Subject	Root mean square	variance	Simple square integral	Standard deviation	Power	Integrated EMG
elbow extension	0.14	0.01	30.7	0.09	5.0	190.9
elbow flexion	0.56	0.21	557.3	0.44	87.7	1017.3
Abduction	0.17	0.02	49.1	0.11	5.9	278.9
Adduction	0.14	0.01	28.6	0.09	4.5	216.3

Table 5.9 Comparison of extracted parameters for triceps muscle

Subject	Root mean square	variance	Simple square integral	Standard deviation	Power	Integrated EMG
elbow extension	0.15	0.01	27.3	0.09	8.4	209.5
elbow flexion	0.21	0.03	86.4	0.14	18.1	339.7
Abduction	0.23	0.04	123.7	0.19	16.4	443.4
Adduction	0.40	0.09	269	0.28	43.2	662

The proposed neural network (ANN) structure based on different hidden layers was considered to find out their applicability for surface electromyogram signal based classification. It was found that 3 neurons in the hidden layer were optimum in terms of complexity and response time. The classification performances were analyzed for different architectures based on number of input features, learning algorithm, number of hidden layers, correlation between input and targets along with mean square error. Finally, the performance parameters of neural network classifiers were calculated and are tabulated in Table 5.10.

Table 5.10 Classification values of ANN model for different hidden layers

Hidden layers	Training Rate	Testing Rate	Classification rate
3	96.4%	83.3%	92.5%
6	89.3%	83.3%	87.5%
9	89.3%	83.3%	87.5%
12	78.6%	83.3%	77.5%
15	67.9%	100%	75.0%

The findings demonstrate that Elbow flexion (ef) and adduction (add) were the two operations which were observed to be easy to be realized by prosthetic devices and 92.5% of best classification success rate was achieved for classification of aforesaid types of upper arm motions from surface electromyogram signals using artificial neural network model, and suggested that the application of Neural Network analysis produced reliable system. The test performance of the Artificial Neural Network model was determined by the computation of the following statistical parameters:

- ✓ The specificity is the percentage of correct classification predicted by model (92.5%).
- ✓ The sensitivity is the percentage of inputs model respondeded (88.8%).
- ✓ Total classification accuracy: percentage of corrected classification rate (92.5%).

The classification of surface electromyogram signal for recognition of upper arm motions with Linear Discriminating Analysis and Artificial Neural Network classifiers were compared. It is tabulated in Table 5.11.

Table 5.11 Comparison of ANN and LDA models for signal classification

Statistical parameters	ANN (%)	LDA (%)
Specificity	92.5%	93.3%
Sensitivity	88.87%	70.0

Total classification accuracy	92.5%	87.50%

A classification accuracy of 87.5% was obtained with discriminating analysis; however, more acceptable classification performance rate of 92.5% was achieved using neural network classifier which also helps in reducing the time needed for obtaining the classification results for discriminating the type of arm motion being used.

The classification efficiency was very high for elbow flexion and adduction movements (90%) and was low for abduction and elbow extension movements (60%). Based on these results, a conclusion could be drawn that aforesaid used network algorithm can be helpful for interpretation of surface electromyogram signal to acceptable levels of the subjects for discrimination of motions for prosthetic design. The results are consistent and reliable since system is tested by taking surface electromyogram signals from number of subjects.

6

DEVELOPMENT AND OPERATION OF PROSTHETIC DEVICE

6.1 Block Diagram and Circuit Description of Hand

Block diagram of electronic circuit for the operation of hand is as given in Figure 6.1.

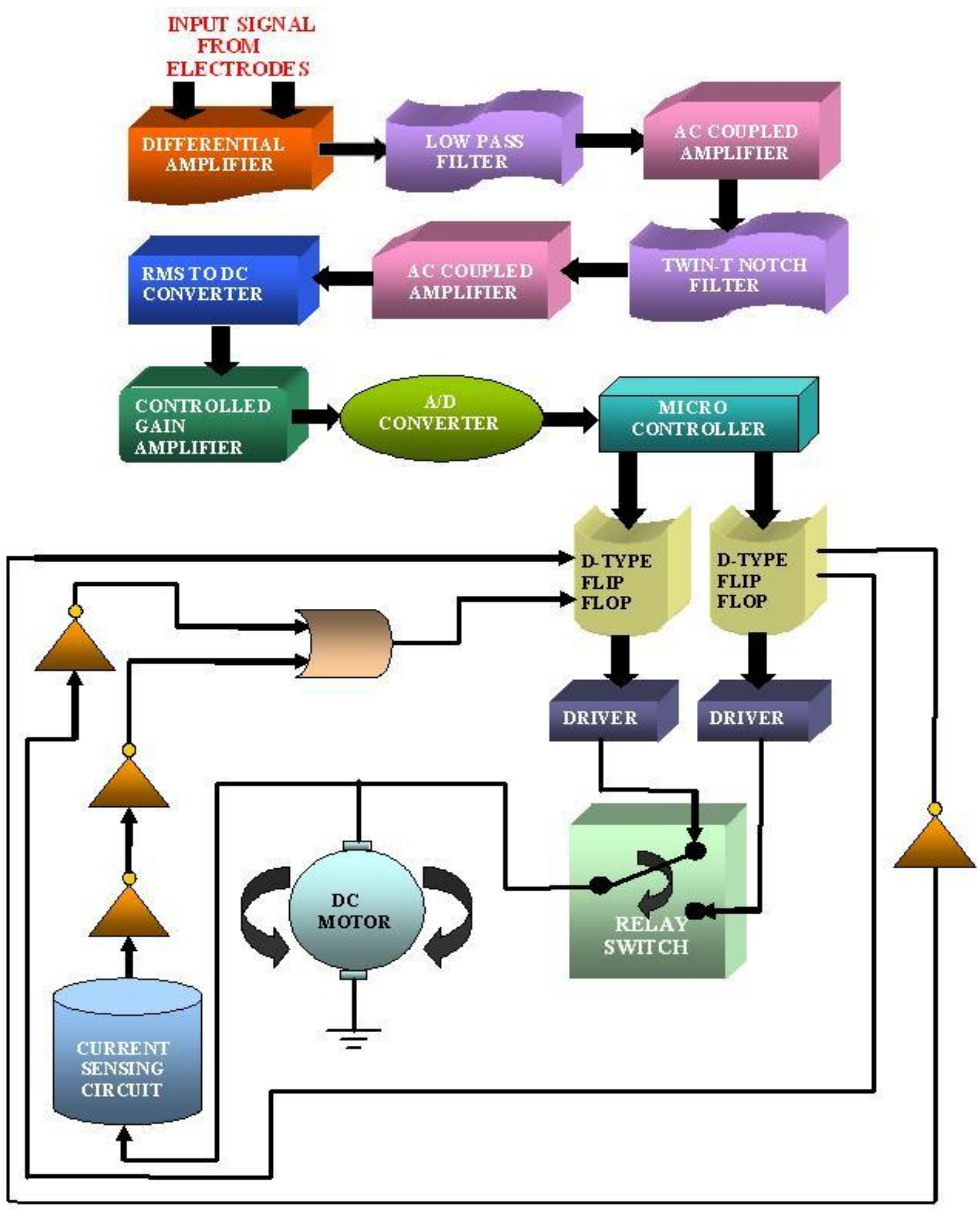


Fig. 6.1 Block diagram for myoelectric arm

Description of various modules of this setup is as below:

6.1.1 DIFFERENTIAL AMPLIFIER

The signal obtained from the electrodes is of the order of microvolts. It is transmitted to the pre - amplification circuitry through shielded cables to reduce transmission losses (Figure 6.2).

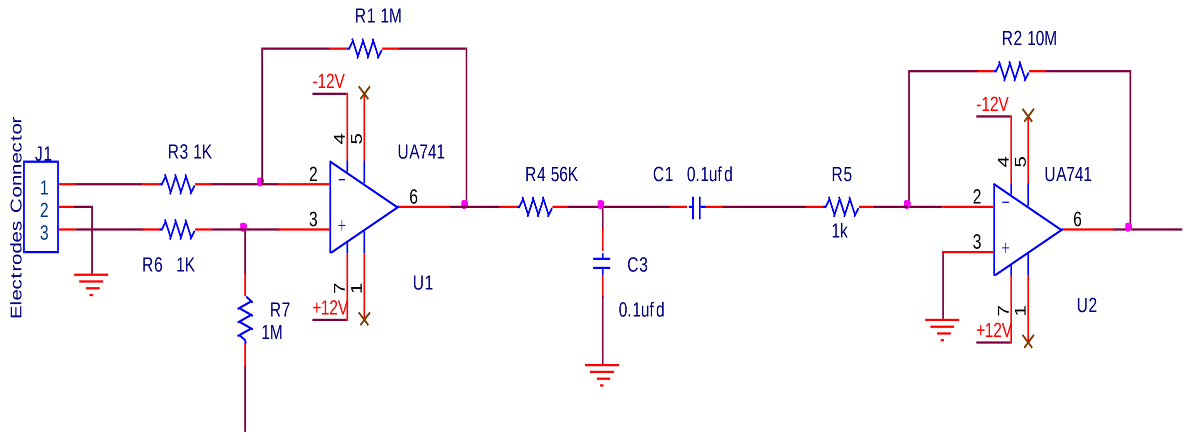


Fig. 6.2 Circuit diagram of amplification stage

The purpose of differential amplifier is to get the difference of muscle contraction between the two locations of the arm. The signals from both electrodes are fed to an amplifier which takes care of common mode noise. During testing, the reference voltage has been set at 3.04 V. This configuration resolves the difference more precisely and makes the output more sensitive to the change in the state of the hand. Even a small relaxation or contraction of the hand shows a measurable variation in the surface electromyogram signal potential.

The voltage gain of the Differential Amplifier is given as

$$A_v = -R_f / R_1$$

6.1.2 LOW PASS FILTER

Since the myoelectric potential used for control is so small, there can be problem from outside interferences like 50 Hz electrical noise. There are many sources of noise which are strong enough to operate the prosthesis erroneously. These include radio signals, static electricity etc apart from power line ripples. A filter removes all these noise signals. The passive RC low-pass filter has a cut off frequency of about 100 Hz.

6.1.3 AC COUPLED AMPLIFIER AND NOTCH FILTER

This amplifier is used to increase the gain further so that signal can be properly analyzed. The gain of this stage is about 100. The notch filter (notch at 50 Hz) eliminates any interference due to nearby power lines.

6.1.4 RMS TO DC CONVERTER

This is used to convert the AC value into proportional DC value, so that the signal level may be properly converted into equivalent digital value. The AD 536 is a complete monolithic integrated circuit which performs true RMS-to-DC conversion. It offers performance which is comparable or superior to that of hybrid or modular units costing much more. The AD 536 directly computes the RMS value of any complex input waveform containing ac and dc components. Its features are:

- True RMS-to-DC Conversion
- High Accuracy
- Single or dual supply operation
- dB output with 60 db range
- Monolithic integrated circuit
- Supply Voltage: 5 V to 36 V

There is full protection for both inputs and outputs. The input circuitry can take overload voltages well beyond the supply levels. Loss of supply voltage with inputs connected will not cause unit failure. The only external component required to perform measurements to fully specified accuracy is a capacitor which sets the averaging period. The most salient feature of true RMS-to-DC converter is that it ideally has no error due to an indirect approximation to the RMS.

6.1.5 ANALOG TO DIGITAL CONVERTER

This analog signal is converted into digital number by an 8-bit A/D converter so that the signal level may be fed to microcontroller to analyze it. The circuit consisting of amplifier RMS to DC Converter and ADC is shown in Figure 6.3.

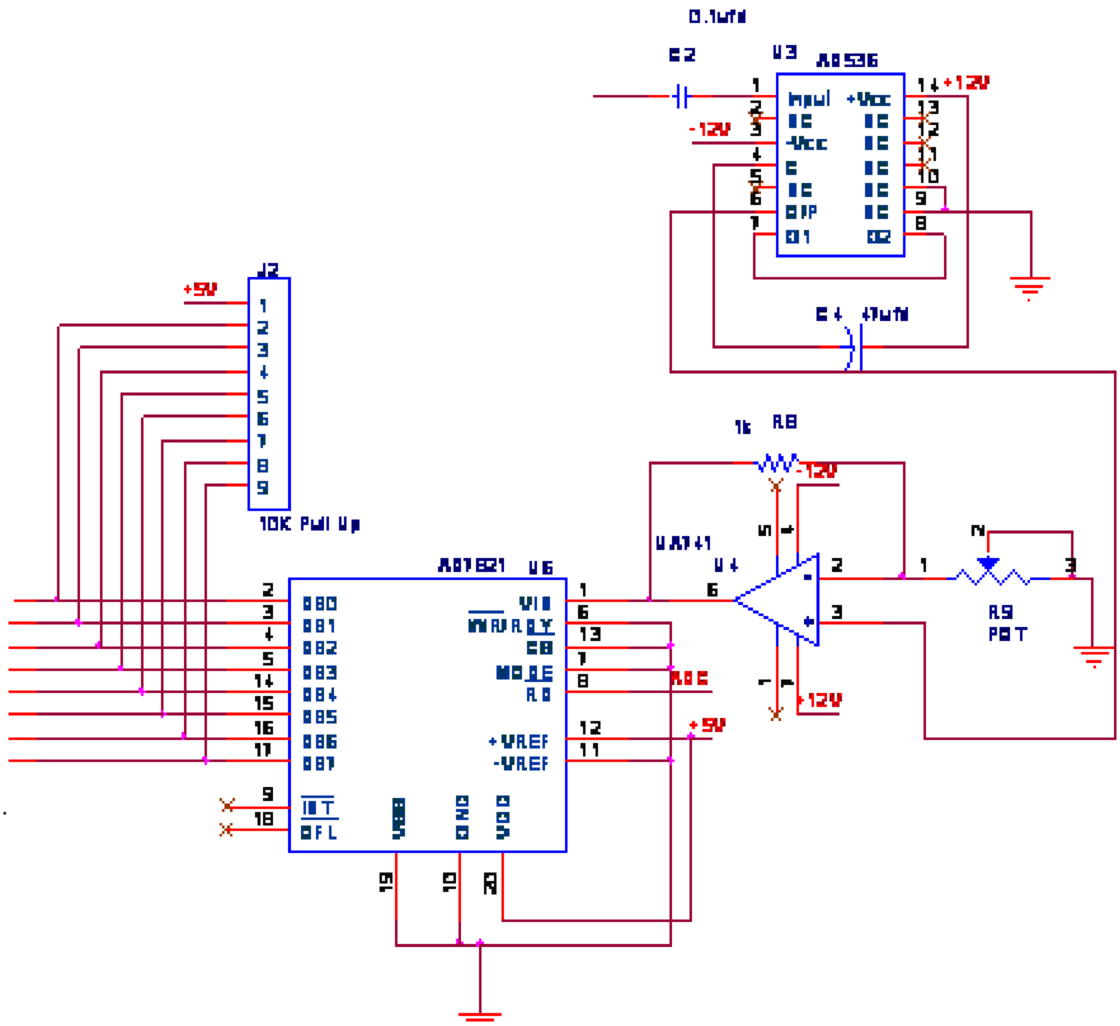


Fig. 6.3 Circuit diagram with ADC stage

6.1.6 MICROCONTROLLER

The 20 pin microcontroller 89C2051 is used here in view of less space available. It controls all the operation sequences like motor operations, controlling relay switching matrix etc.

6.2 CONTROL OF GRIPPING FORCE

The developed myoelectric arm is similar to natural arm as it has the feature of variable gripping force i.e. the force applied by the hand fingers on the object is proportional to the weight of the object. To implement the feature, a relay switching system was designed which consisted of relays meant for closing and opening the hand to switch different values of resistances in series with motor armature (Figure 6.4). Two relays are used for opening and closing limit switches and another two relays are used for implementation of grip control logic function. This function depends on the activation of particular relay switching at different time instants, according to the instructions received from microcontroller. The logic is set for three different levels of forces. Grip 1 is the lowest level logic, Grip 2 is for medium level logic and Grip 3 is for high level logic. Based on the surface electromyogram signal exerted by the user, different resistances are selected by a relay matrix which varies the current through the motor thus varying the torque which in turn, manifests itself as grip force.

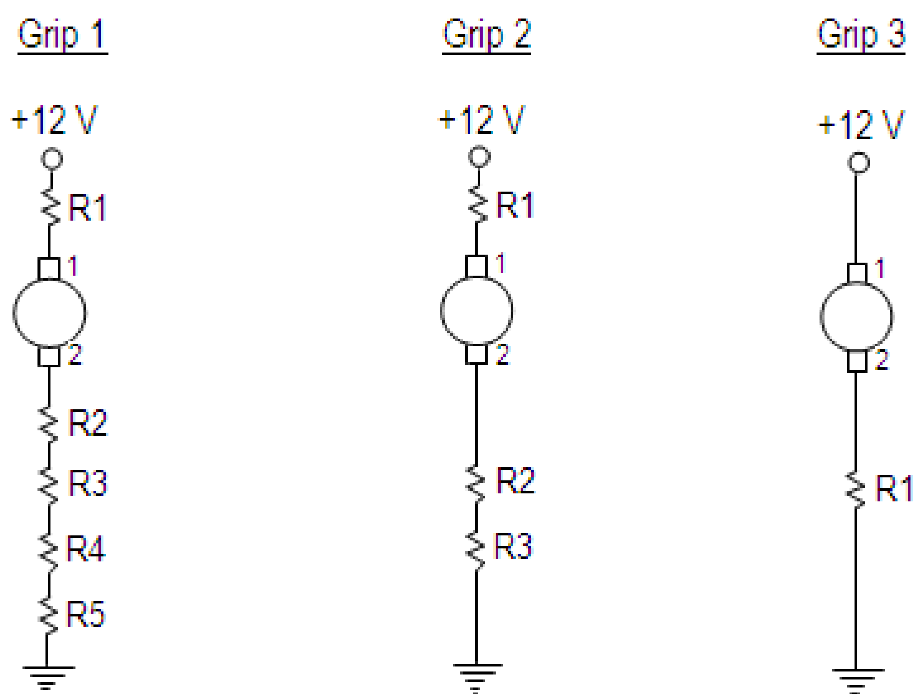


Fig. 6.4 Gripping logic

6.3 REMOTE CONTROL BASED ELBOW MOVEMENT

The whole electronics for elbow movement is divided in two parts - RF Transmitter (TWS-434) with switches and RF Receiver (RWS-434). In RF transmission circuitry, four switches were used. These switches were followed by an encoder (HT 12E) and RF transmitter module which AM modulates the 434 MHz carrier frequency and transmits RF modulated wave onto a small antenna.

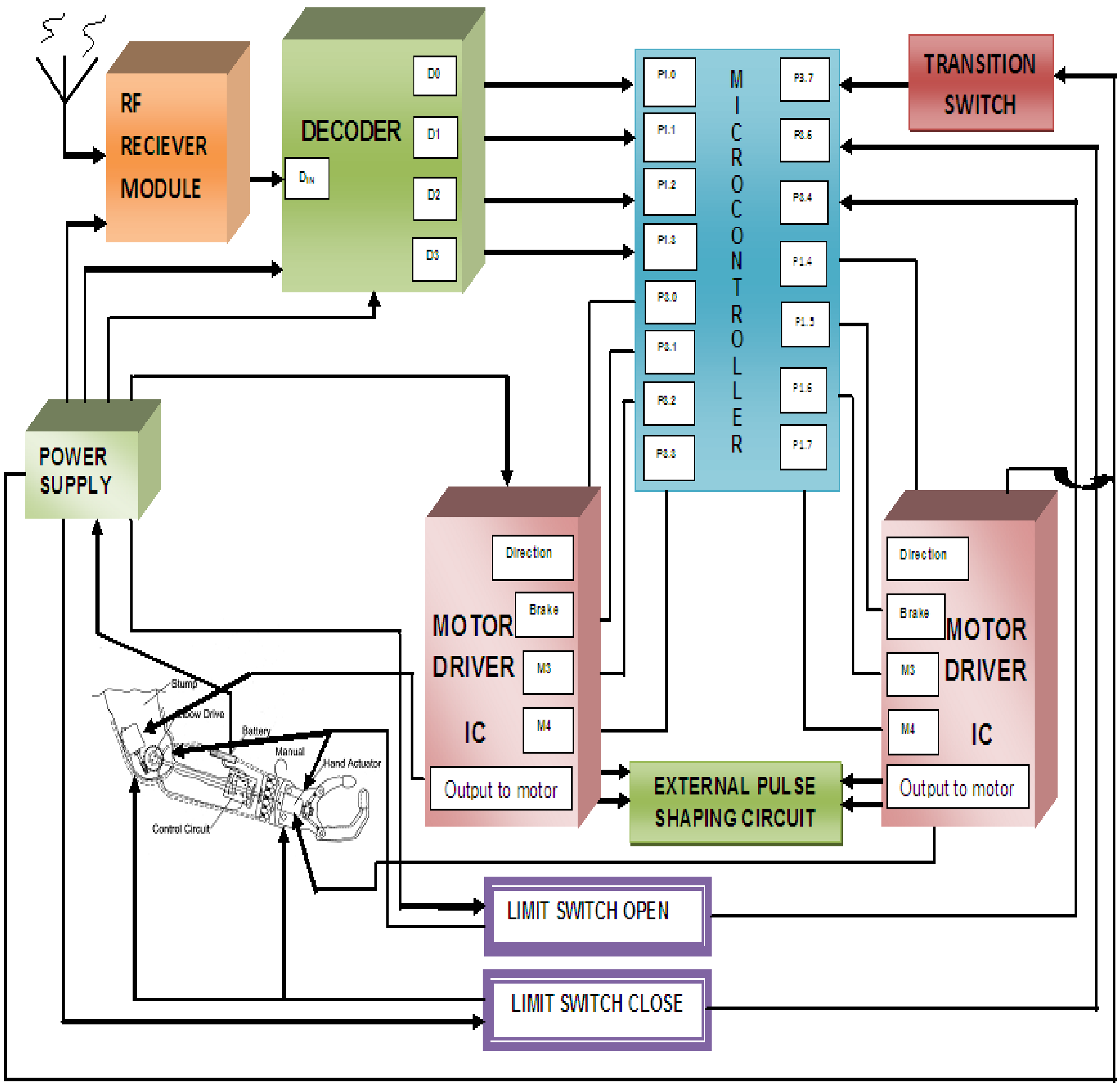


Fig. 6.5 Block diagram of RF receiver with elbow movement controlled circuitry

RF Receiver module mounted on the hand performs the reverse operation (Figure 6.5). It decodes the modulated signal and drives the elbow motor using suitable driver circuits.

6.4 TESTING AND OPERATION OF THE DEVICE

The fabrication and testing of the designed arm was carried out in the laboratory. Experimentally, the frequency components up to 40 Hz were found to undergo change due to muscle action. The signal was, low-pass filtered up to 100 Hz and amplified to increase the sensitivity. The amplitude of amplified EMG was found as 0.4 - 0.8 volts in the relaxed state and 2.3 – 4.0 volts during contraction in different subjects. To offset the variability of signal, a variable gain amplifier was designed, which was used to set the gain less than 1 volt signal in relaxed state and more than 2.5 volt during contraction. The threshold between opening and closing of hand was then set to 2 volts. The motor current during normal closing of hand was recorded as 67 mA which rises to more than 500 mA when an object is gripped. A threshold of 400 mA was set to cut-off the motor supply.

When the lifted object is seen by eye it gives signal to brain. In response, the brain gives the signal to arm muscles providing the information about how much heavy the object is and accordingly, the muscle contracts. This contraction is sensed by electrodes and this electromyogram signal is provided to microcontroller in digital form. The microcontroller drives the relay matrix according to the signal strength.

When power of the complete system is put ON, the current position of hand is detected through microcontroller with the help of optical limit switches; microcontroller then restores the hand to the default ‘CLOSE’ position. If hand is already ‘CLOSED’ no action is taken by microcontroller. Surface electromyogram signal initiated by the user is consistently and continuously scanned by microcontroller and thereafter hand starts opening with predefined speed and grip force. After full opening of hand, controller again waits for close signal from the user. As user generates the close signal, the hand starts closing and grips the object with a grip force proportional to induced level of surface electromyogram signal by the user. To implement variable grip force, current in the armature of motor is varied using a matrix of resistors with the help of relay switching. Different port bits of the microcontroller for different relay operations are set or reset as shown in Table 6.1

Table 6.1 Different microcontroller port-bits function

Grip 1: Lowest grip force		
TH1<= SEMG signal<= TH2		
P3.0 = 0	P3.2 = 0	Motor ‘ON’
P3.1 = 0	P3.2 = 1	Motor ‘OFF’
Grip 2: Medium grip force		
TH2<= SEMG signal<= TH3		
P3.0 = 1	P3.3 = 0	Direction for ‘OPEN’ set
P3.1 = 0	P3.3= 1	Direction for ‘CLOSE’ set
Or		
P3.0 = 0	P3.4=0	‘Open’ limit switch reached
P3.1 = 1	P3.4=1	‘Open’ limit switch yet not reached
Grip 3: Highest grip force		
SEMG signal >= TH3		
P3.0 = 1	P3.5=0	‘Close’ limit switch reached
P3.1 = 1	P3.5=1	‘Close’ limit switch yet not reached

TH_1, TH_2 and TH_3 denote the progressively increasing threshold levels of surface electromyogram signal corresponding to three different increasing grip forces exerted by hand on the object. One relay is used for the opening and closing of the hand by changing the direction of motor, while second relay is for making the motor On/Off and another two relays implement the grip force logic function. Based on the surface electromyogram signals exerted by the user, microcontroller bits control different relays which, in turn, put different resistances in series with motor to control the current through motor thus achieving variable grip force. The complete circuit diagram for myoelectric arm is depicted in Figure 6.6 while flow chart for the working of myoelectric control based prosthetic device with following categories is shown in Figure 6.7.

Case 1- Hand is open originally and has to close (Grip process)

In this case, by relay switching system, direction is set for “CLOSE” position. Surface electromyogram signal has to be then exerted by subject approximately for less than 2s before relaxing.

Case 2- Hand is closed originally and has to open

If the applied force is more than a particular threshold value i.e. TH_{open}, it means subject is trying to open hand and then Grip 3 is set and consequently motor gets "ON" and direction of hand for "OPENING" is set.

Case 3 -Hand closed, it is to be opened - Releasing object

This is just like case 1.

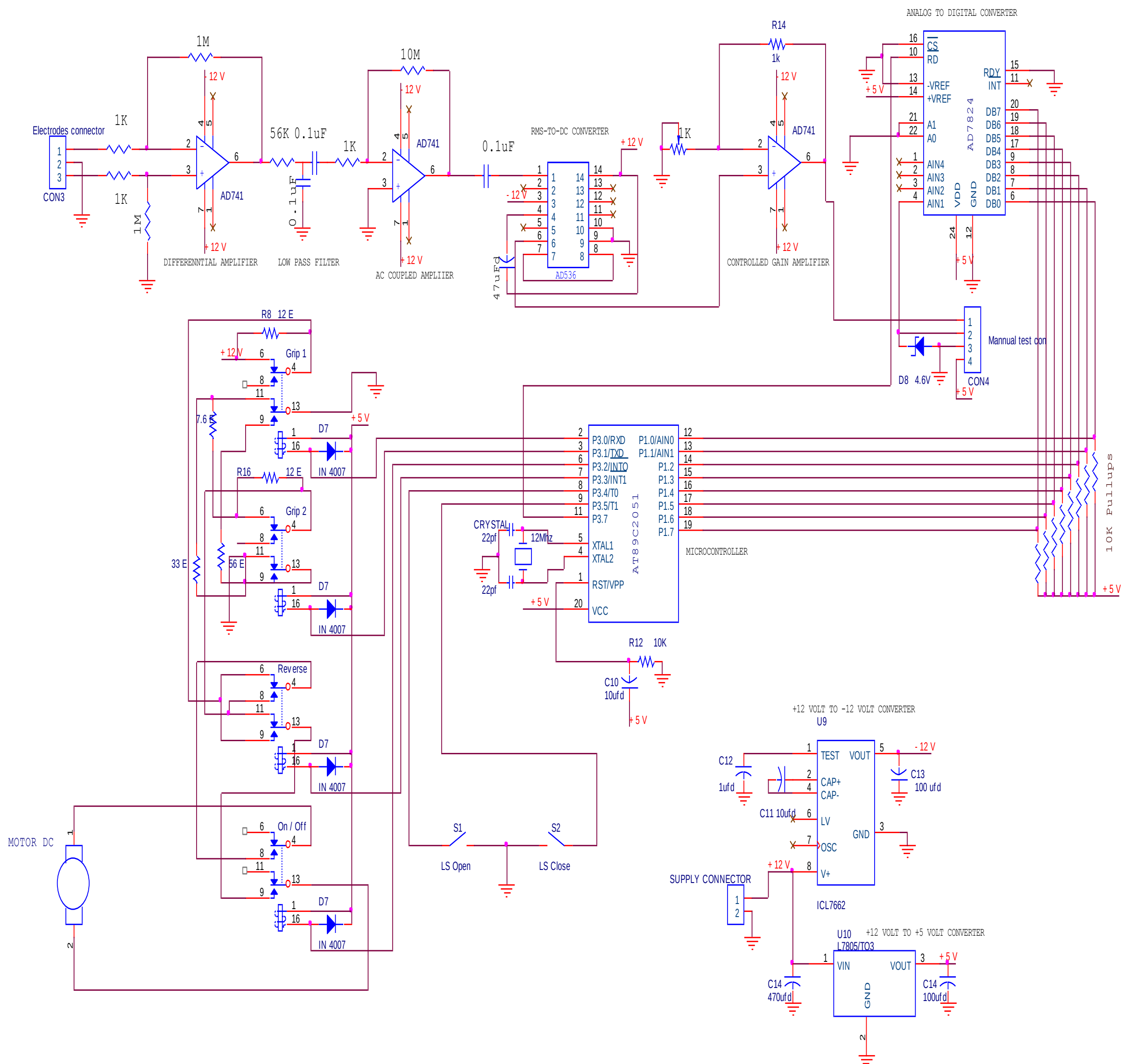


Fig. 6.6 Complete Circuit Diagram of Myoelectric Arm

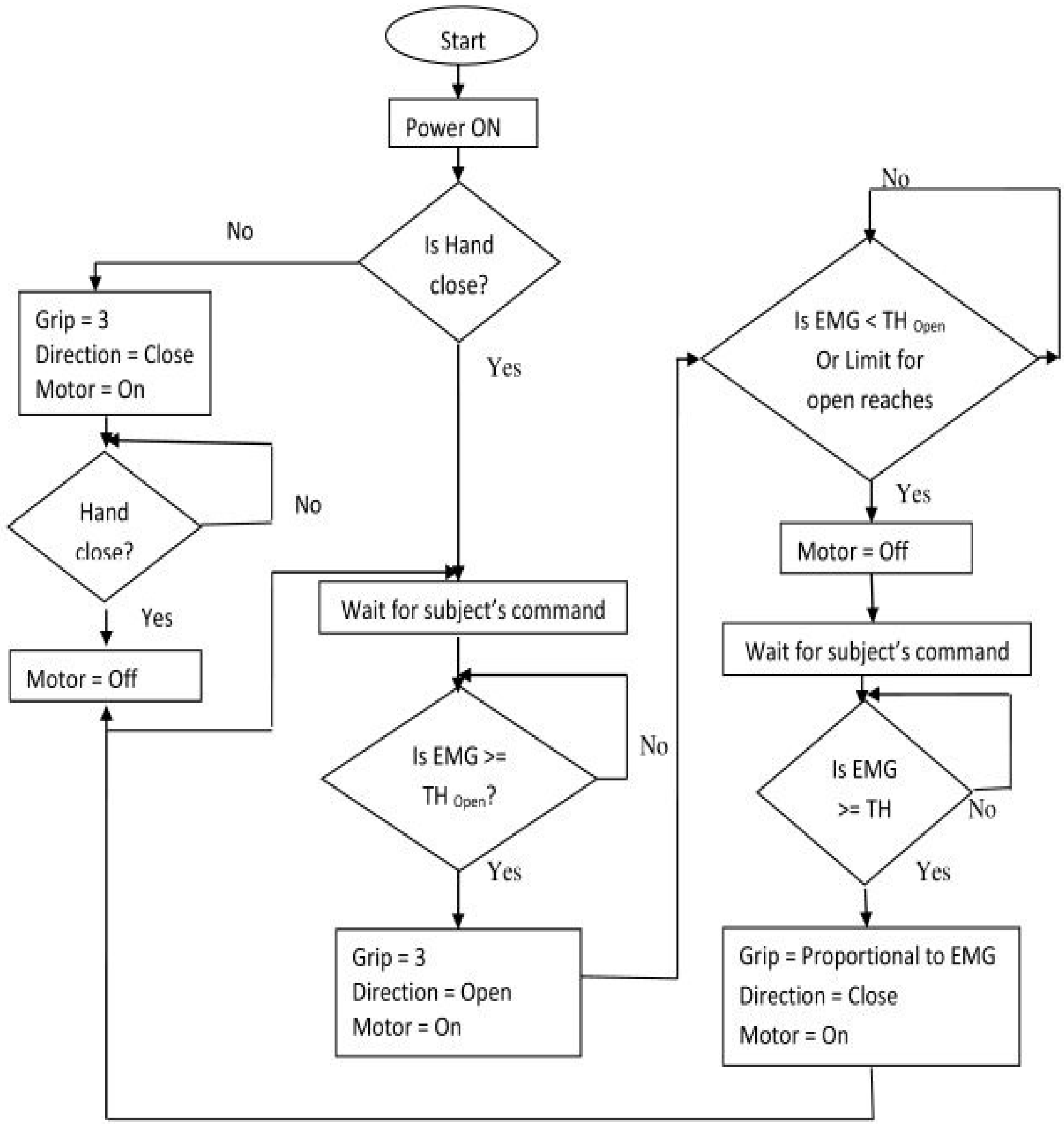


Fig. 6.7 Flow chart for the complete operation of myoelectric arm

The mechanical assembly of the arm consisted of wrist, palm and the fingers to grip the object in addition to a screw arrangement connected to a low power D.C. motor and gear assembly to open or close the hand. The wrist is mechanically rotated with the other hand to orient the artificial hand in a direction suitable to pick up the object. The entire set up is placed in a casing which provides a cosmetic appeal to the artificial hand and the connected arm.

6.5 ELECTRODE PLACEMENT

For proper signal acquisition, electrode placement on the arm is very important. This requires accurate identification of the muscle. After thorough study and experimentation, biceps and triceps muscles of the residual limb were identified from which appreciable signal was obtained during voluntary contraction. Three gold plated surface electrodes were mounted above these muscles - one as reference, another as active and the third as ground electrode. For better contact between electrode and muscle, we used a conducting jelly. Experiments were made to optimally place these electrodes and to identify the proper point of axial spread of muscle where the amplitude of signal was maximal.

The electrodes (Figure 6.8) cannot be placed axially along the muscles of the arm because the stump length available from such patients is not enough. The placement of this assembly in the transverse direction led to the difficulty that the surface of arm was not uniform throughout the radial span of the stump; it was rather curved. Also at the time of relaxation and contraction of the muscle, this curvature varies and the electrodes could not be fixed properly to pick the signal from a particular point. During experiments with this assembly, it was noted that if electrodes are placed very close to each other, active and reference electrodes pick up almost the same signal from the same muscle causing no difference between them. For this reason, to get substantial signal, we placed the electrodes as far as possible from each other in the transverse direction. The arm setup in the lab is shown in Figure 6.9 and the complete below-elbow arm in Figure 6.10.

Fig. 6.8 The three electrodes

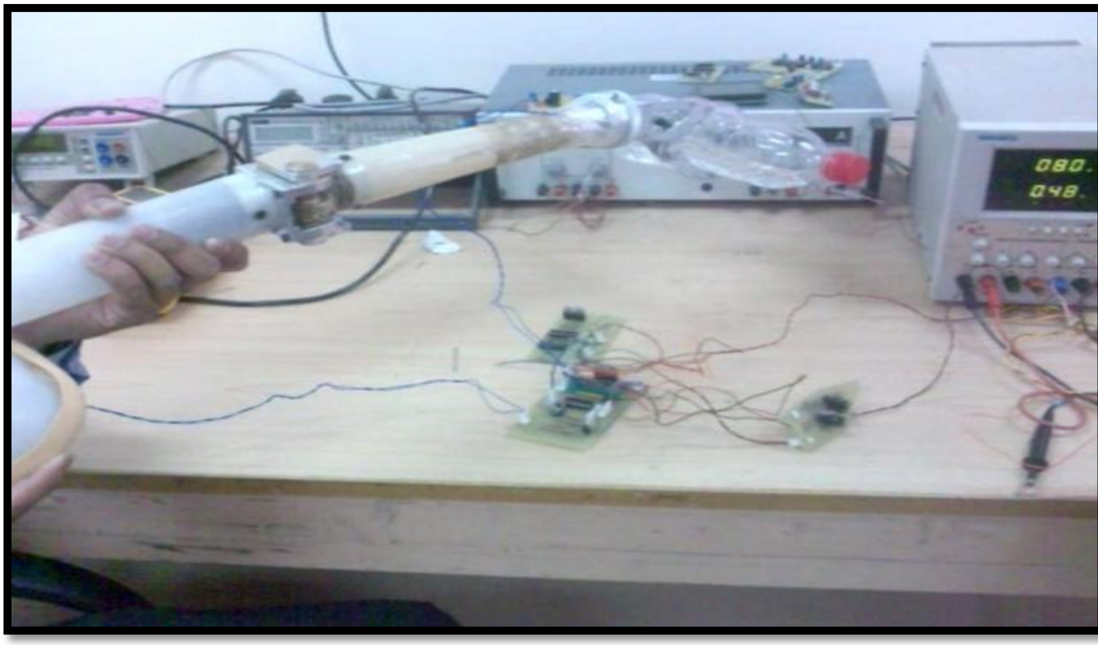


Fig. 6.9 Lab set up and circuit diagram for arm

Fig. 6.10 Below-elbow myoelectric arm

7 CONCLUSION AND FUTURE SCOPE

Prosthetics are important to improve amputees' lifestyles and researching new strategies control over the prosthetic appendage. Surface EMG is used for the study of muscle activities and to develop myoelectric prosthesis in the present investigation.

Implementation of the electromyogram amplifier device, surface EMG recording technique and development of artificial device were discussed in detail in previous pages. The study of different parameters in relation to surface EMG variations with force level was carried out and found that both, amplitude related parameters and selected statistical parameters gave good insight into the force level exerted by muscles. The surface EMG amplitude based parameter resulted into linear variations up to around 90% of the maximum voluntary contraction of a subject.

7.1 SEMG INTERPRETATION

The surface electromyogram signals on multi-channel muscle locations for four independent activities were investigated. The designed system for acquiring surface electromyogram signal was used for the purpose of extracting as many motor unit action potential trains as possible with the greatest level of accuracy and finally interpretation of signal was done to estimate the effect of signal variations for different positions and for multiple motions.

Surface electromyogram frequency based variation remains constant in a narrow band. So the aim was to present effectiveness of algorithms to extract features of the surface electromyogram signal during voluntary contractions for possible applications. The Euclidean distance (ED) based muscle separation index is used in class separability of arm movements in feature space. It may be observed that the performance of the classification for different arm motions is obtained best when the ED's value is high, further, the statistical parameter Mutual Separation Index becomes large to indicate better performance. Since the purpose of this technique was to find factors which improve control assistive devices or prosthesis from surface electromyogram signals, it can be concluded that statistical measured index is, additionally, an effective way for expressing surface electromyogram signal's feature evaluation index.

Further, Fourier Transform is not suitable for the non stationary signals since it fails to provide the frequency component occurring at desired interval while it gives the information of amount of frequency content existing in the signal. Instead, Discrete Wavelet Transform (DWT) offers an effective multi resolution property for analyzing the nonstationary signals as it computes the coefficients at discrete level instead of all levels. The surface electromyogram signal is nonstationary in nature so the objective was to find suitable wavelet in an order to classify the arm motions producing these signals. The evaluation methods used for the classification of arm movements can be considered as alternative tool for the design of muscular system based upper arm prosthetic devices. The wavelet denoising for formal interpretation is used optimally for the interpretation of surface electromyogram signal. Wavelet- based noise removal is preferred over signal frequency domain filtering because it can maintain signal characteristics even while reducing noise. This is because a number of threshold strategies are available, allowing reconstruction based on selected coefficients.

The research work reported here utilizes double channel signal detection setup and shows the success rate for classifying surface electromyogram signals with back propagation training algorithm. Since the objective was to implement surface electromyogram signals for classification of upper arm motions, so the effectiveness of the recorded and extracted feature set were explored using Linear Discriminant Analysis (LDA) and Artificial Neural Network (ANN) classifiers respectively. A classification accuracy of 87.5% was obtained with discriminating analysis; however, more acceptable classification performance rate of 92.5% was achieved using neural network classifier and which also helps in reducing the time needed for obtaining the classification results for discriminating the type of arm motion being used. The classification efficiency was very high for elbow flexion and adduction movements (90%) and was low for abduction and elbow extension movements (60%). Based on these results, a conclusion could be drawn that aforesaid used network algorithm can be helpful for interpretation of surface electromyogram signal to the acceptable levels of the subjects for discrimination of motions for prosthetic design. The results were consistent and reliable since system is tested by taking surface electromyogram signals from a number of subjects.

Next, as the electrical activity of muscles being measured by surface electromyogram exhibits non-linearity, it was thought that the statistical theory may be a better approach than traditional linear methods in characterizing the intrinsic nature of signal. This type of characterization can contribute to the understanding of the signal dynamics and underlying muscle processes. The signal interpretation utilizing computing techniques was applied to compare variation among data and the results showed significant variation among data for stated groups. The statistical analysis (Analysis of Variance technique and Principal Component Analysis) was considered using sum of squares of deviations of data points from their sample means. Elbow flexion (ef) and adduction (add) were the two operations which were observed to be easy to be realized by prosthetic devices. From the results, it was also interpreted that Body Mass Index (BMI) range has very little effect on signal value for higher contraction, where the amplitude of surface electromyogram signal increases progressively as a function of time for different type of movements.

To summarize:

(i) The surface myoelectric signal force relationship is primarily determined by different muscle geometries including electrode configuration, fiber diameter and subcutaneous tissue thickness *etc*.

(ii) There exists linear relationship between muscular signal and force contraction till fatigue occurs

(iii) Electrode placement finds significant role in establishing relationship between muscle site and concerned movement

(iv) Amplification and processing of surface electromyogram signal is necessary before it is to be used

(v) Among explored wavelets,db4 performs better and is suitable for accurate classification of surface electromyogram signal

(vi) Mean and Median frequency increase as contraction level increases till fatigue occurs

7.2 PROSTHETIC DESIGN

The relevant aspects covered under the development of arm constitute two stages –first stage, the signal conditioning with controlling and second stage, its mechanical assembly. Electronic design consisted of analog and digital signal processing and controlling circuit. The electromyogram signal from the residual stump of the subject was picked up through surface electrodes, amplified and artifacts were removed in a controlled manner so that minimum signal loss occurs due to processing. Further, before evaluating and interpreting surface electromyogram signal, the Fast Fourier Transform was analyzed, as it provides information about the frequency contents in the signal.

The mechanical assembly consisted of wrist, palm and the fingers to grip the object in addition to a lead screw arrangement connected to a low power D.C. motor and gear assembly to open or close the hand. The wrist is mechanically rotated to orient the hand in a direction suitable to pick up the object. The entire set up is placed in a casing which provides a cosmetic appeal to the artificial hand and the connected arm. The surface electromyogram signal based fabricated arm with three different grip force patterns on subjects was tested successfully. The subjects were quite comfortable in opening and closing of hand according to the muscle activity and could hold the object and place it at different place with ease. Even it had the capability to reverse its motion from the ongoing direction as the natural hand does. Implementation of this type of system gives the prosthetic user capability to perform different tasks with maximum efficiency in daily living. A load of up to 1.5 kg can be lifted by the developed device.

The specifications of designed prosthetic device are as follows:

Operating Voltage	:	6V / 9 V
Current Consumption	:	200 mA (Approx.)
Opening Width	:	75-100 mm
Grip Force	:	50 N (max.)
Average Speed	:	3-4cm/sec. (approx.)
Weight of arm	:	1.7 kg
Weight lifting capacity	:	2 kg (max)
On-off switch	:	Integrated

7.3 FUTURE SCOPE

For the future development of the surface electromyogram technologies, following suggestion are made:

1. Although the value of surface electromyogram has been proven in fundamental researches and for specific diagnostic purposes, there is as yet no broad clinical application. Multi-electrode grid can be the better solution for movement discrimination.
2. To remove the motion artifacts from wired electrode systems, wireless sensor network technologies are likely to produce better results.
3. The grip force levels may be further increased for more smoothening of hand's grip.
4. The processors with high programming capabilities can be used to handle large data from surface electromyogram electrodes and to analyze these data for future use. The system's sensitivity needs to be further improved.
5. The classification efficiency of the system could be increased by the fine tuning of sampled data and with increase in the input bits by implementing on dedicated microcontroller system.
6. More study on reliability of acupressure or other similar techniques *e.g* acupuncture points needs to be carried out. This will help in establishing surface electromyogram sites on the skin for specific movements.
7. The validation of the obtained results on more subjects would increase the authenticity of results.
8. Prosthetic devices can be developed by using newly discovered alloys or composite materials as they are light weight and hard enough to meet the requirements. The greatest advantage is the ease of machining.
9. The study on energy efficient motors, driving circuits and couplings can further improve the degree of functionalities of prosthetic devices.
10. Performance of whole system can be improved if low torque motor is replaced by high torque; higher efficiency motor so that in future heavy objects may be manipulated.

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