ANALYSIS AND CLASSIFICATION OF EMG SIGNAL USING LabVIEW WITH DIFFERENT WEIGHTS

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Electronics Instrumentation and Control

Submitted by

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DECLARATION

I hereby certify that the work which is being presented in the dissertation entitled, "**ANALYSIS AND CLASSIFICATION OF EMG SIGNAL USING LabVIEW WITH DIFFERENT WEIGHTS**" in partial fulfilment of the requirements for the award of degree of masters of engineering in Electronics Instrumentation and Control Engineering submitted in Electronics Instrumentation and Control Engineering Department, Thapar university, Patiala, is an authentic record of my own work carried out under the supervision of **Mr. Nirbhow Jap Singh**, Assistant Professor and **Dr. Ravinder Agarwal**, Professor, Department of Electrical and Instrumentation Engineering, Thapar University, Patiala, Punjab.

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Dedicated to My Parents and Brothers

ABSTRACT

Prosthetic is a branch of biomedical engineering that deals with missing human body parts with artificial one. The present research work is broadly divided in two parts namely; detection and classification of EMG signals and replacement of missing body parts. Further, the work carried out is related to feature extraction and classification of EMG signals obtained from bicep and below elbow position. The EMG signals are obtained for different cases: Grasping and Lifting, with different weight combinations. The SEMG signal is obtained from the surface of the body by using disposable electrodes. For the acquisition of SEMG signal BIOKIT Datascope system is used. The features are extracted from the conditioned EMG signal such as: root mean square value, integrated EMG value, mean absolute value and zero crossing rate.

The signals are usually non-repeatable and contradictory in nature. Therefore, to classify such kind of signal, a classifier able to withstand uncertainties in data is required. Fuzzy theory is well known for its capability to deal with imprecise environment. So, in this work a fuzzy classifier is designed and implemented using LabVIEW software. The classifier system is tested using 30 subjects. The simulation results have authenticated the capability of implemented system.

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CHAPTER 1
INTRODUCTION

Electromyography (EMG) is an experimental technique concerned with the development, recording and analysis of myoelectric signals. Myoelectric signals are formed by physiological variations in the state of muscle fiber membranes.

An unfiltered and unprocessed signal detecting the superimposed motor unit action potential (MUAPs) is called a raw EMG Signal. A raw surface EMG recording (SEMG) using static contractions of the biceps brachii muscle is shown in the Fig. 1.1.

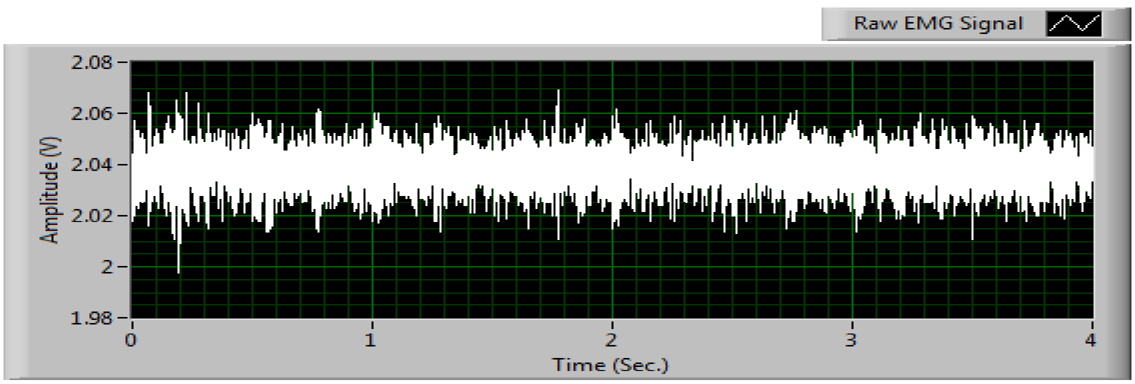

Fig. 1.1 Raw EMG signal

In the relaxed state of muscle, a more or less noise-free EMG baseline is observed in EMG plot. The raw EMG baseline noise depends on many factors, especially the quality of the EMG amplifier, the environmental noise and the condition of subject under investigation. In case a state of the art amplifier is available and skin is properly prepared, the averaged baseline noise should not be higher than 3 to 5 microvolts, 1 to 2 achievable. The investigation of the EMG baseline quality is a very important checkpoint of every EMG measurement. Interfering noise or problems within the detection apparatus may results in increased base activity or muscle.

The healthy relaxed muscle shows no significant EMG activity due to lack of depolarization and action potentials. The raw EMG spikes are usually random in shape, which means one raw recording burst cannot be precisely reproduced in exact shape. This is due to the fact that the actual set of recruiting motor units constantly changes within the matrix/diameter of available motor units. If suddenly two or more motor units are fired at the same time and they are located near the electrodes, a strong superposition spike is produced. The application of a smoothing algorithm (*e.g*. moving average filter) or selecting a proper amplitude parameter (*e.g*. area under the rectified curve), eliminates non- reproducible contents of the signal.

A raw SEMG signal ranges between ±5000 μV and typically frequency contents 6 - 500 Hz and the most of frequency power is between 20 and 150 Hz.

Besides basic physiological and biomechanical studies, SEMG is established as an evaluation tool for applied research, physiotherapy/rehabilitation, sports training and interactions of the human body to industrial products and work conditions is as shown in Fig. 1.1.

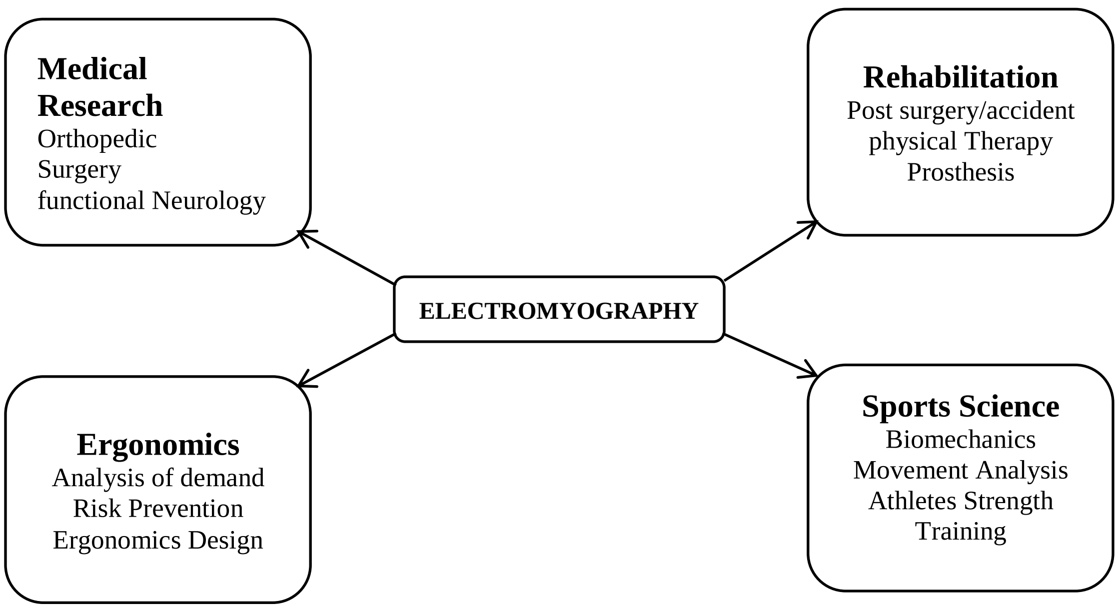

Fig. 1.2 Block diagram of SEMG research fields

In 1940's an application of EMG signal was deployed for prosthesis control. The prosthesis is of many types but EMG signal is used as input for the control of power prosthesis. The signal is used to select and modulate a function of a multifunction prosthesis [1].

1.1 Prosthesis

Prosthesis is artificial substitute for a missing part of the body. The artificial parts that are most commonly thought of as prostheses are those that replace lost arms and legs, but bone, artery, heart valve replacements are common and artificial eyes and teeth are correctly termed prostheses.

The medical specialty that deals with prostheses is called prosthetics. The origin of prosthetics as a science is attributed to the 16^{th}-century French surgeon **Ambroise Pare [2]**. Later workers developed upper-extremity replacements, including metal hands made either in one piece or with movable parts. The solid metal hand of the 16^{th} and 17^{th} centuries later gave way in great measure to a single hook or a leather-covered, nonfunctioning hand attached to the forearm by a leather or wooden shell .Improvement in the design of prostheses and increased acceptance of their use have accompanied major wars. New lightweight materials and better mechanical joints were introduced after World Wars I and II.

The different prostheses developed by the main prosthetic societies: UTAH, OTTA BOCK and PROTEOR concentrate 90% of the market. These are classified in three categories namely; aesthetic prostheses, body-powered prostheses and myoelectric prostheses.

1.1.1 Aesthetics Prosthesis

This type of prosthesis is generally used by patients and their aim is only aesthetics. The prosthetic part is created from a standard mold and resemblance to the healthy member. This kind of prosthesis does not carry out any movement. It only serves to restore the patient's body appearance. This kind of prosthesis is far instance manufactured by the OTTO BOCK society.

1.1.2 Body-powered Prostheses

A body-powered prosthesis, also known as conventional or cable-driven prosthesis, is powered and controlled by gross body movements. This movement usually of the shoulder, upper arm, or chest is captured by a harness system and used to pull a cable that is connected to a TD (hook or hand). For some levels of amputation or deficiency, an elbow system can be added to provide additional motion. For a patient to control a body-powered prosthesis, the individual must be capable of producing at least one or more of the following gross body movements:

1.1.3 Myoelectric Prostheses

Myoelectric signals (Electromyogram or EMG) are electrical signals that are registered for muscular activities. A large number of applications are possible with these signals. The functional motor activities can be measured by placing the surface electrodes directly on the skin. The EMG signals are complex with noise and they are easily influenced by many factors. The EMG signal requires several treatments before it can be interpreted and used. UTAH society was the first to propose the EMG technology to control the prosthesis. The OTTO BOCK society also proposes prosthesis of hand coupled with a myoelectric elbow. Unfortunately, the whole system proposed by this society is too expensive for the patient. The hand is a tree legs grip with an aesthetic glove [3].

1.2 Algorithms for EMG Classification

The control of assistive devices and exoskeletons using EMG signals has been the focus of many researchers. As EMG signals are complex in nature, EMG classification for motion detection is a challenging task. The various approaches used to efficiently classify the EMG signals are summarized as follows (1) Neural network (2) Fuzzy logic (3) Hybrid fuzzy-neural approaches and (4) Particle swarm optimization-SVM based.

In presented work fuzzy logic approach are used for classification of EMG signals. There has been many works on fuzzy approaches to EMG classification. Fuzzy logic has the ability to deal with imprecise, uncertain and imperfect information. The strength of fuzzy logic lies in the fact that it is based on the reasoning inspired by human decision-making. This fuzzy logic is used to handle the vagueness intrinsic to many problems by representing them mathematically. Fuzzy logic systems are advantageous in biomedical signal processing and classification. Biomedical signals are not always strictly repeatable, and may sometimes even be contradictory. One of the most useful properties of fuzzy logic systems is that contradiction in the data can be tolerated. Furthermore using trainable fuzzy systems, it is possible to discover patterns in data, which are not easily detected by other methods, as, can also be done with neural network. Other neural network approaches are discussed in literature work.

In the presented work the objective of EMG signal classification is achieved in a step wise approach. The signals from subjects are acquired using single channel Biokit system. The acquired signals are processed using LabVIEW for feature extraction. The signal processing performed involves signal amplification, signal filtration and sampling using analog to digital converter.

To classify processed EMG signal, a fuzzy logic based classifier is developed by LabVIEW 2012 (evaluation version). The performance of developed classifier is evaluated using available test data acquired from subjects in lab. The test data is obtained from two points (1) flexor carpum ulnaris (below elbow) for gripping and (2) biceps brachhi (between elbow and shoulder) for lifting movements of different weights.

The presented work organized in 6 chapters. First chapter is an introduction of EMG signals, EMG signals for prosthesis and algorithms of classification in the field of EMG signal classification. Chapter 2 consists of literature review, to study the EMG signal analysis and classification. It presents some time domain and frequency domain feature extraction techniques of EMG signal. It provides guideline to design the fuzzy classifier for this application. Chapter 3 summarized the material and methods used for acquisition of signal and classification. Chapter 4 consists of the solution methodology, Setup of signal acquisition, feature extraction and design classifier for EMG signal. In chapter 5 results are presented and designed classifier is tested with 180 EMG signals so that the success rate of the classifier can calculate. Chapter 6 concludes the presented work and future scope is summarized.

CHAPTER 2
LITERATURE REVIEW

Kelly *et al*. [4] described some early work done to explore the application of neural networks to the myoelectric signal analysis. Hopfield algorithm was used to compute the time series parameters of the moving average signal model. The performance of two algorithms, namely the Hopfield and Sequential Least Squares algorithm were compared and it was concluded that Hopfield was two to three times faster than the latter based on a typical EMG data. Some additional results such as the use of perceptron in the future myoelectric signal analysis were also discussed.

Nishikawa and Kuribayashi *et al.* [5], Used neural network to discriminate hand motions for EMG-Controlled Prostheses. Here the neural network was used to learn the relation between EMG signal's power spectrum and the motion task desired by the handicapped subjects

Hudgins *et al.* [6], Analyzed the EMG signals for controlling multifunction prosthesis. Features were extracted from several time segments of the myoelectric signal to preserve pattern structure. These features were then classified using an artificial neural network. They observed that the performance of their system enhanced due to the neural network's ability to adapt to small changes in the control patterns.

Francis H. Y. Chan *et al.* [7], proposed a fuzzy approach to classify single-site electromyography (EMG) signals for multifunctional prosthesis control. While the classification problem was the focus of the paper, the ultimate goal was to improve myoelectric system control performance, and classification was an essential step in the control. Time segmented features were fed to a fuzzy system for training and classification. In order to obtain acceptable training speed and realistic fuzzy system structure, these features were clustered without supervision using the Basic Isodata algorithm at the beginning of the training phase, and the clustering results were used in initializing the fuzzy system parameters. Afterwards, fuzzy rules in the system were trained with the back-propagation algorithm. The fuzzy approach was compared with an artificial neural network (ANN) method on four subjects, and very similar classification results were obtained. It is superior to the latter in at least three points: slightly higher recognition rate;

Kiguchi *et al.* [8], Developed a fuzzy controller to control the elbow and shoulder joint angles of the exoskeleton based on the moving average value of EMG signals from arm and shoulder muscles and the generated wrist force. Nearly 50 fuzzy IF-THEN control rules were designed based on the analyzed human subject's elbow and shoulder motion patterns in the pre-experiment.

Weir, R. Fff *et al.* [9], developed a new multifunctional prosthetic hand mechanism that will be interfaced to the user using a four site myoelectric (EMG) controller based on fuzzy logic techniques. Three to four independent EMG sites (the maximum number that could be isolated without the cross-talk becoming unacceptable) were used to control three or four degrees-of-freedom (DOF) in the prosthetic hand. Fuzzy logic techniques were used to detect EMG onset and classify user intent. Membership functions for each EMG channel were based on EMG signals acquired during a training session. Standard clinical techniques were used to locate the four sites. Rules recognizing the different EMG levels associated with a particular function are automatically generated based on the recorded EMG training data. Results of experiments comparing this controller with other control algorithms used in prosthetics control were presented. The implemented controller was capable of providing seamless sequential control i.e. sequential control without the intermediate switching steps with an update rate of 50 msec.

Abidemi Bolu Ajiboye *et al.* [10], presented a heuristic fuzzy logic approach to multiple electromyogram (EMG) pattern recognition for multifunctional prosthesis control. Basic signal statistics (mean and standard deviation) were used for membership function construction, and fuzzy c-means (FCMs) data clustering was used to automate the construction of a simple amplitude-driven inference rule base. Other algorithms in current literature assume a longer period of unperceivable delay, while the system presented had an update rate of 45.7 ms with little post processing time, making it suitable for real-time application. Five subjects were investigated (three with intact limbs, one with a unilateral transradial amputation, and one with a unilateral transradial limb-deficiency from birth).

Four subjects were used for system offline analysis, and the remaining intact-limbed subject was used for system real-time analysis. They discriminated between four EMG patterns for subjects with intact limbs, and between three patterns for limb-deficient subjects. Overall classification rates ranged from 94% to 99%. The fuzzy algorithm also demonstrated success in real-time classification, both during steady state motions and motion state transitioning. This functionality allowed for seamless control of multiple degrees-of-freedom in a multifunctional prosthesis.

Kazuo Kiguchi *et al.* [11], developed robotic exoskeletons to assist motion of physically weak persons such as elderly, disabled, and injured persons. The robotic exoskeleton is controlled based on the electromyogram (EMG) signals, since the EMG signals of human muscles are important signals to understand how the user intends to move. Even though the EMG signals contain very important information, however, it is not very easy to predict the user's upper-limb motion (elbow and shoulder motion) based on the EMG signals in real-time because of the difficulty in using the EMG signals as the controller input signals. They proposed a robotic exoskeleton for human upper-limb motion assist, a hierarchical neuro-fuzzy controller for the robotic exoskeleton, and its adaptation method.

Ahmet Alkan *et al.* [12], presented a classification technique that classifies signals required for a prosperous arm prosthesis control by using surface EMG signals. This work used recorded EMG signals generated by biceps and triceps muscles for four different movements. Each signal has one single pattern and it is essential to separate and classify these patterns properly. Discriminant analysis and support vector machine (SVM) classifier have been used to classify four different arm movement signals. Prior to classification, proper feature vectors are derived from the signal. The feature vectors are generated by using mean absolute value (MAV). The feature vectors were provided as inputs to the identification/classification system. Discriminant analysis using five different approaches, classification accuracy rates achieved from very good (98%) to poor (96%) by using a 10-fold cross validation. An SVM classifier gives a very good average accuracy rate (99%) for four movements with the classification error rate 1%. Correct classification rates of the applied techniques are very high which can be used to classify EMG signals for prosperous arm prosthesis control studies.

Abdulhamit Subasi *et al.* [13], presented a novel PSO-SVM model that hybridized the particle swarm optimization (PSO) and SVM to improve the EMG signal classification accuracy. This optimization mechanism involved kernel parameter setting in the SVM training procedure, which significantly influences the classification accuracy. The experiments were conducted on the basis of EMG signal to classify into normal, neurogenic or myopathic. In the proposed method the EMG signals were decomposed into the frequency sub-bands using discrete wavelet transform (DWT) and a set of statistical features was extracted from these sub-bands to represent the distribution of wavelet coefficients. The obtained results validated the superiority of the SVM method compared to conventional machine learning methods, and suggest that further significant enhancements in terms of classification accuracy can be achieved by the proposed PSO-SVM classification system. The PSO-SVM yielded an overall accuracy of 97.41% on 1200 EMG signals selected from 27 subject records against 96.75%, 95.17% and 94.08% for the SVM.

Siti A. Ahmad *et al.* [14], presented a state based Fuzzy Logic classifier. They used the information from states of contraction to determine the final output state for the system. The states are start, middle and end of contraction. This classifier uses two SEMG signals as the control channel where the amputees have to do wrist flexion, wrist extension and co-contraction, and all these movements could be performed at their convenience. The classification results indicate that fuzzy logic system could discriminate different output based on the states of contraction. From the investigation, it observed that, this type of classifier could give a more robust classification result especially in the middle of a contraction, compared to the start and end of a contraction.

Yousef Al-Assaf *et al.* [15], in this paper, a method that does not use any a priori knowledge of hypotheses parameters to detect the transient change in MES signals was presented. That based on sequentially estimating the dynamic cumulative sum of generalized likelihood ratios. In order to allow detection of any frequency or energy changes, DCS is applied after signal decomposition on scales of a multi-scale representation using the Coiflet orthogonal wavelet with five different scales. Polynomial classifiers are used to classify four elbow and wrist movements using the single MES channel. The input features for the classifiers were obtained using Multi resolution wavelet analysis. Even with a single recording channel, promising continuous classification accuracy with adequate control system response time is achieved. The use of more recording channels, testing the proposed method in more subjects and studying feature extraction techniques that require shorter analysis time are venues for future research.

Hardeep S. Ryait *et al.* [16], described measurement of SEMG depends on a number of factors/parameters like amplitude, time and frequency domain properties. In the present investigation, analysis was carried (1) study the grip force vs. SEMG parameters at acupressure points on the arm, using single channel approach. At all the selected acupressure points a linear increment of SEMG was observed. (2) discriminate four elbow movements from different locations on the arm using two channel approach with single parameter. The parameter for the analysis chosen was the root of mean of square (RMS) value of SEMG. Further; principal component analysis was used to verify the elbow movement discrimination. Extension and supination were the two operations which were observed to be easy to realize by prosthetic devices. The selection of these locations was done on the basis of acupressure points and anatomy of the elbow.

Luay Fraiwan *et al.* [17], presented a start point for training patient to use prosthetic devices using virtual reality prosthesis. The proposed system consists mainly of an electromyography (EMG) system connected to the patient's arm (biceps and triceps muscles) and interfaced with a PC using a data acquisition system. The PC uses Matlab to enhance the EMG signals and detect the presence of events in them. These events are used to control a virtual hand with two movements; grasping and wrist rotation. The system was tested on a subject who performed the grasping and wrist rotation for 90 trials. The overall success rate was found to be 84%.

HaeOck Lee *et al.* [18] discussed externally powered upper extremity prosthesis as a system. The necessary components to design a better prosthetic arm were divided into four subsystems: input, effecter, feedback. That was reviewed in terms of these subsystems. Each subsystem performs its own task, but they are related to each other and together they function to make up a prosthetic upper extremity, which provides the movement to the amputee.

Deepak Joshi *et al.* [19], discussed the trends undergoing in all the various steps involved in EMG (Electromyogram) based prosthetic hand development. In order to overcome some limitations of current prosthetic hands mainly related to the proper functionality and controllability, the prosthetic hand has been designed following a bio mechatronic approach based on biologically inspired design solutions. The majority of electrically powered prosthetic hands were based on a simple design that limits motion to one degree of freedom. Designs of multi-articulated prosthetic hands have had limited success due to their complexity and number of mechanical components. Classical EMG (myoelectric) controllers had failed in the past, since they were based on only determining existence or non-existence of an EMG signal. Recent work has approached this multifunctional control problem using a large number of electrodes, though still considering only a limited part of the EMG spectrum.

S. Herle *et al.* [20], present an algorithm based on an autoregressive (AR) model representation and a neural network, for EMG signal classification. The results have shown that combining a low-order AR model with a feed forward neural network, a rate of classification of 98% can be achieved, while keeping the computational cost low. The solution proposed is capable of controlling three joints (i.e. six movements) of the upper limb prosthesis. The inputs of the high-level controller are obtained from the classifier, while its outputs are applied as input signals for the low-level controller.

Ulvi Baspinar *et al.* [21], in this study, a home-made four channel sEMG amplifier circuit were designed for measuring EMG signals. The recorded sEMG signals were filtered with a band pass filter and afterwards wavelet based filtering was applied to remove unwanted noises. As a second step, the recorded and de-noised signals' features were extracted. For classification of motions 8 time domain and 2 frequency domain features were used. There is no reduction applied to the features for artificial neural network (ANN) classification while the features were reduced in two dimension using by Diffusion Map for fuzzy classification. Lastly, seven different motions were classified by

ANN and Gustafson Kessel algorithm. Also, their classification performances were compared.

Phan Anh Phong *et al.* [22], this paper proposed a method to construct type-2 Takagi-Sugeno-Kang (TSK) fuzzy system for electrocardiogram (ECG) arrhythmic classification. The classifier is applied to distinguish normal sinus rhythm (NSR), ventricular fibrillation (VF) and ventricular tachycardia (VT). Two features of ECG signals, the average period and the pulse width, are inputs to the fuzzy classifier. The rule base in the fuzzy system is constructed from training data. They also presented the method using fuzzy C-mean clustering algorithm and the back-propagation technique to determine parameters of type-2 TSK fuzzy classifier. The generalized bell primary membership function is used to examine the performance of the classifier with different shapes of membership functions. The results of experiments with data from the MIT-BIH Malignant Ventricular Arrhythmia Database show the classification accuracy of 100% for NSR signals, 93.3% for VF signals, and 92% of VT signals.

J. Rafiee *et al.* [23], presented a new technique for feature extraction of forearm electromyographic (EMG) signals using a proposed mother wavelet matrix (MWM). A MWM including 45 potential mother wavelets is suggested to help the classification of surface and intramuscular EMG signals recorded from multiple locations on the upper forearm for ten hand motions. Also, a surface electrode matrix (SEM) and a needle electrode matrix (NEM) are suggested to select the proper sensors for each pair of motions. For that purpose, EMG signals were recorded from sixteen locations on the forearms of six subjects in ten hand motion classes. The main goal in classification is to define a proper feature vector able to generate acceptable differences among the classes. The MWM included the mother wavelets, which make the highest difference between two particular classes.

Six statistical feature vectors were compared using the continuous form of wavelet packet transform. The mother wavelet functions are selected with the aim of optimum classification between two classes using one of the feature vectors. The locations where the satisfactory signals were captured were selected from several mounted electrodes.

Finally, three ten-by-ten symmetric MWM, SEM, and NEM represent the proper mother wavelet function and the surface and intramuscular selection for recording the ten hand motions.

Abidemi Bolu Ajiboye *et al.* [24], proposed an algorithm based upon neuro-fuzzy technology. We believe that because of the inherent “fuzziness” of human activity, a control algorithm based on fuzzy logic may have advantages for multifunctional prosthesis control. They seek an acceptable compromise between the number of electrode sites used and processing complexity, and thereby desire not more than three to four control sites to control three to four DOF. This approach delivers more information to the system and, by using fuzzy logic, reduces the complexity of the processing.

Lars H. Lindstrom [25], Electromyography is the art of describing myoelectric signals. These signals are the electric manifestation of the excitation process preceding the mechanical contraction in the muscles. The myoelectric signal, observed with surface electrodes or coaxial needle electrodes, is composed of so-called action potentials originating from the individual muscle fibers. The fibers of the muscle are functionally organized in subgroups, so-called motor units. The activity of each unit was controlled by a motoneuron located in the spinal cord with its axon extending to the muscle.

Foster B. Stulen *et al.* [26], during a sustained muscle contraction, the spectrum of the myoelectric signal is known to undergo compression as a function of time. Previous investigators have shown that the frequency compression is related to the decreasing conduction velocity of the muscle fibers. It proposed that the frequency compression might be tracked by obtaining a continuous estimate of a characteristic frequency of the spectrum, such as the mean and median, or the ratio of low-frequency components to high-frequency components of the spectrum. A theoretical analysis was performed to investigate the restrictions in estimating the three parameters, as well as their sensitivity to the conduction velocity. A technique is described, which determines an unbiased consistent estimate of the median frequency.

David T. Gibbons *et al.* [27], the use of EMG signals from residual muscles to control above-elbow prosthesis has been tried, but presents many problems, not the least being that the prosthesis is under open-loop control. A more satisfactory control technique is extended physiological proprioception where the inherent proprioceptive feedback present within an intact joint is used to provide closed-loop control. Our technique is to control the positioning of this above elbow prosthesis using the motion of the intact shoulder. Grasp, which does not involve positioning in space is separately controlled using EMG signals from biceps and triceps muscles. A choice from a range of linkages can enable the user to perform different tasks in different situations.

Edward A. Clancy *et al.* [28], temporal whitening of individual surface electromyography waveforms and spatial combination of multiple recording sites have separately been demonstrated to improve the performance of EMG amplitude estimation. This investigation combined these two techniques by first whitening, then combining the data from multiple EMG recording sites to form an EMG amplitude estimate. A phenomenological mathematical model of multiple sites of the surface EMG waveform, with analytic solution for an optimal amplitude estimate, is presented. Experimental surface EMG waveforms were then sampled from multiple sites during non-fatiguing, constant-force, isometric contractions of the biceps or triceps muscles.

R. Merletti *et al.* [29], the reproducibility of surface myoelectric signal measurements is of paramount importance for clinical applications of electromyography (EMG) techniques. The repeatability of electrically-evoked myoelectric signal shape as well as spectral and amplitude parameters, conduction velocity and elicited torque were tested, in isometric conditions. Contractions were elicited by stimulation of the main muscle motor point and repeated after removal and replacement of the stimulation and detection electrodes in the same carefully marked locations. This protocol was repeated five times on each subject on five different days.

C. P. Fermo *et al.* [30], this work presents the development of a sensor for detecting human muscle contraction, which captures myoelectric signals (EMG), in order to control a myoelectric prosthesis of superior limb. It is proposed a strategy for controlling the artificial hand, based on the myoelectric signal. This way, the patient has a more accurate and easier control of the movement of the prosthetic device, thus leading to a faster adaptation. Through a proposed control strategy, a method to analyze the pattern of the myoelectric signal can be defined. Thus, several kinds of actuating of the artificial hand can be obtained by a simple binary signal or through the analysis of the myoelectric signal pattern.

S. Venkataramanan *et al.* [31], myoelectric control refers to the use of processed Electromyogram (EMG) signals in the operation of devices external to the human body. A variety of myoelectric controller algorithms exist, but there is immense scope for optimization. This paper proposes a new intelligent system which is capable of optimizing the system speed and the number of actions that can be selected. The optimization involves rigorous mathematical analysis of the characteristics and the interdependence of these two parameters. The intelligent systems employ a technique continuously monitor the actions that are performed. Accordingly, they allocate the least selection duration to those actions that are executed the most number of times

Wendy Franks B *et al.* [32], a low electrode-electrolyte impedance interface is critical in the design of electrodes for biomedical applications. To design low-impedance interfaces a complete understanding of the physical processes contributing to the impedance is required. In this work a model describing these physical processes is validated and extended to quantify the effect of organic coatings and incubation time. Electrochemical impedance spectroscopy has been used to electrically characterize the interface for various electrode materials.

Mahdi Khezri *et al.* [33], Electromyogram signal (EMG) is an electrical manifestation of contractions of the muscles. Surface EMG signal collected from the surface of the skin has been used in diverse applications. One of its usages is exploiting it in a pattern recognition system, which evaluates and synthesizes hand prosthesis movements. The ability of the current prosthesis has been limited in simple opening and closing that decreases the efficacy of these devices in contrary to natural hand. In order to extend the ability and accuracy of prosthesis arm movements and performance, a novel approach for SEMG pattern recognizing system is proposed.

Ishibuchi, H. *et al.* [34] This paper presented how the rule weight of each fuzzy rule could be specified in fuzzy rule-based classification systems. First, they proposed two heuristic methods for rule weight specification. Next, the proposed methods were compared with existing ones through computer simulations on artificial numerical examples and real-world pattern classification problems. Simulation results show that the proposed methods outperform the existing ones in the case of multiclass pattern classification problems with many classes.

Ishibuchi, H. *et al.* [35] This paper examines the effect of rule weights in fuzzy rule-based classification systems. Each fuzzy IF-THEN rule in our classification system has antecedent linguistic values and a single consequent class. They used a fuzzy reasoning method based on a single winner rule in the classification phase. The winner rule for a new pattern is the fuzzy IF-THEN rule that has the maximum compatibility grade with the new pattern. When they use fuzzy IF-THEN rules with certainty grades, the winner is determined as the rule with the maximum product of the compatibility grade and the certainty grade, the effect of rule weights was illustrated by drawing classification boundaries using fuzzy IF-THEN rules with/without certainty grades. It is also shown that certainty grades play an important role when a fuzzy rule-based classification system is a mixture of general rules and specific rules. Through computer simulations, they show that comprehensible fuzzy rule-based systems with high classification performance can be designed without modifying the membership functions of antecedent linguistic values when they used fuzzy IF-THEN rules with certainty grades

CHAPTER 3
MATERIAL AND METHODS

The implementation of EMG signal classifier involves, EMG signal acquisition system and software based signal processing and classification system. This chapter describes the electrodes, electrode theory, EMG amplifier, feature extraction, classification and the LabVIEW software used for the analysis and classification of SEMG. SEMG exhibit complex behavior with different complexities. EMG is a very complex signal which is distorted by factors like anatomical and physiological properties of the muscles.

In the present work, SEMG is picked up with the help of electrodes. The signals are analyzed and classified with LabVIEW at two points (1) flexor carpum ulnaris (below elbow) for gripping and (2) biceps brachhi (between elbow and shoulder) for lifting movements of different weights.

3.1 Electrodes

To observe the measurement of EMG, a perception that the measurement electrodes are simply electrical terminals or contact points from which voltages can be obtained at the surface of the body and the electrolyte paste or jelly often used in such measurement reduces skin impedance of the system. It is realized that the bioelectric potential generated in the body are ionic potentials, produced by ionic current flow. Efficient measurement of these ionic potentials led to the development of the modern noise free, stable measuring devices. Devices that convert ionic potential into electronic potentials are called electrodes. The theory of electrodes and principle that govern their design are inherent in an understanding of the measurement of bioelectric potentials.

3.2 Electrode Theory

Action potentials are produced by the movement of ions and can be recorded from outside excitable cells (extracellular recording) because of fields generated close to the active fibers. In order to observe these potentials using electronic instrumentation, they must be transduced into ohmic potentials. This process is mediated by metal conductors.

The electrode-electrolyte interface when a metal disk is placed in an electrolyte solution, an ion electron exchange occurs metal ions enter the solution and electrolyte ions combine with the metal of the electrode resulting in a charge distribution at the metal-electrolyte interface:

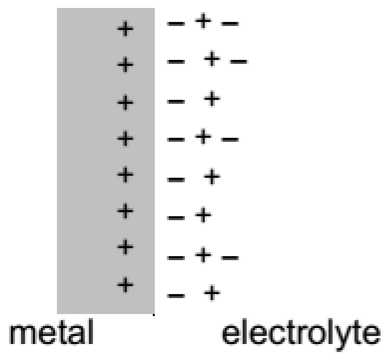

Fig. 3.1 Metal electrolyte interface

A potential, called the half-cell potential is generated as a result of the charge layer. The potential at the electrode interface can only be measured with respect to another electrode; half-cell potentials are measured with respect to a standard electrode called the hydrogen electrode. The hydrogen electrode is formed by platinum in contact with a solution of hydrogen ions and dissolved molecular hydrogen. The hydrogen electrode is defined as having a half-cell potential of zero. If an electrode of one metal is connected to an electrode of another metal, a non-zero potential will exist between them. For example, at 25^{o}C Ni has a half-cell potential E^0= -0.23V and Ag has a half-cell potential E^0= 0.799V. If a Ni and Ag electrode are connected together, the potential difference will be -0.23-0.799 = -1.029V. If a biological potential is recorded using electrodes of different metals, the DC offset may swamp the much smaller biological signal. Thus it is important to use electrodes made of the same metal in contact with the same electrolyte [36].

Half-cell potential will change when current flows between electrodes and electrolyte. The difference between the potential with the current and the equilibrium zero current half-cell potential is called the over-potential. Three components contribute to the over-potential the ohmic over-potential, the concentration over-potential, and the activation over-potential. The ohmic over-potential is the voltage drop between two electrodes in an electrolyte solution, where current is flowing through the solution between the electrodes and the solution has a finite resistance. The resistance of the electrolyte may vary with current, thus the ohmic over-potential may not be linearly related to the current. The concentration over potential arises because the concentration of ions at the electrode-electrolyte interface will change when current passes across the interface. The activation over-potential is due to the difference in activation energy (or energy barrier) that must be overcome for a metal atom to oxidize and enter the electrolyte solution as a cation, and the activation energy required for a cation to be reduced and deposit a metal atom on the electrode surface.

If two electrodes of the same metal are placed in a solution, a large fluctuating potential may exist between the electrodes, because of a small amount of contaminant on one or both electrodes.

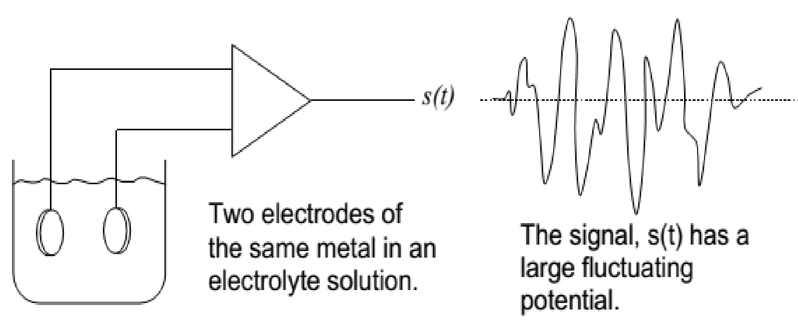

Fig. 3.2 Signal generation by two electrodes of same metal

Silver (Ag) electrodes can be stabilized by electrolytically coating the electrode with a layer of silver chloride (AgCl), Ag-AgCl electrodes are widely used in bio potential recording.

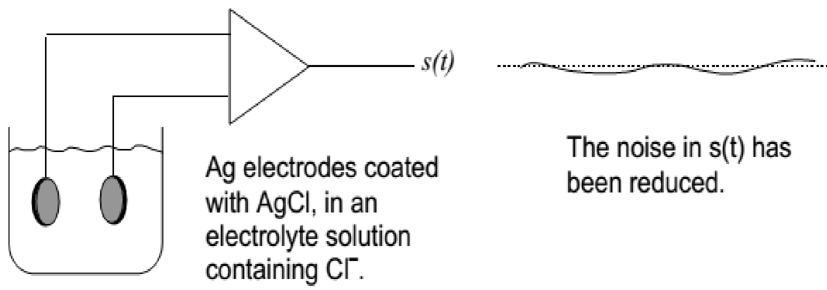

Fig. 3.3 Signal generation by Ag-AgCl solution

The AgCl layer stabilizes the electrode, effectively attenuating the noise between the electrodes, as long as the Ag-AgCl electrode is in contact with an electrolyte solution containing a relatively high concentration of Cl^- ions [37].

3.3 Bio Potentials Electrodes

Over the years many different types of electrodes for recording various potentials on the body surface have been developed. These are mainly classified into three basic types: microelectrodes, skin surface electrodes and needle electrodes.

All three types of bio potential electrodes have the metal electrolyte interface, in each case, an electrode potential is developed across the interface, proportional to the exchange of ions between the metals and the electrolytes of the body.

The chemical activities that take place within an electrode can cause voltage fluctuations to appear within any physiological input. Such variation may appear as noise on a bioelectric signal. The noise can be reduced by proper choice of materials or, in most cases, by special treatment, such as coating the electrodes by some electrolytic methods to improve stability. It has been found that a silver-silver chloride electrode is very stable. This type of electrode is prepared by electrolytically coating a piece of pure silver with silver chloride. The coating is normally done by placing a cleaned piece of silver into a bromide free sodium chloride solution. A second piece of silver is also placed in the solution, and the two are connected to a voltage source such that the electrode to be chloride is made positive with respect to each other. The silver ions combine with the chloride ions from the salt to produce neutral silver chloride molecules that coat the silver electrode. Electrodes used to obtain bioelectric potential from the surface of the body are found in many sizes and forms. Although can be used to sense EMG potentials.

3.3.1 Disposable electrode, one of the most frequently used forms of bio-potential sensing electrodes is the metal-plate electrode. In its simplest form, it consists of a metallic conductor in contact with the skin. An electrolyte soaked pad or gel is used to establish and maintain the contact.

It consists of a relatively large disk of plastic foam material with a silver plated disk on one side attached to a silver-plated snap similar to that used on clothing in the center of the other side. A lead wire with the female portion of the snap is then snapped onto the electrode and used to connect the assembly to the monitoring apparatus. The silver-plated disk serves as the electrode and may be coated with an AgCl layer. A layer of electrolyte gel covers the disk. The electrode side of the foam is covered with an adhesive material that is compatible with the skin. A protective cover or strip of release paper is placed over this side of the electrode and foam, and the complete electrode is packaged in a foil envelope so that the water component of the gel will not evaporate away. To apply the electrode to the patient, the clinician has only to clean the area of skin on which the electrode is to be placed, open the electrode packet, snap the lead wire on to the electrode, remove the release paper from the tack, and press the electrode against the patient's skin. This procedure is quickly accomplished and no special technique need be learned. Fig. (3.4) is shows the disposable electrode.

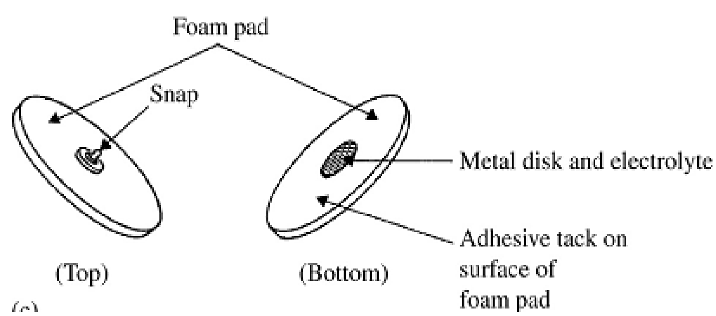

Fig. 3.4 Disposable electrodes

In the presented work disposable electrodes were used. Disposable electrode is an electrode that requires skin preparation for ignoring the artifacts. Alcohol were used for skin cleaning then electrode were placed to the position of flexor carpum ulnaris (below elbow) for gripping and biceps brachhi (between elbow and shoulder) for lifting movements at different forces.

These disposable electrodes connect to the Datascope amplifier through the 5 pin male connector of Datascope.

Fig. 3.5 Five pin male connector socket

3.4 Biokit Datascope System

The Biokit Datascope system is used for capturing and analyzing SEMG signals. The captured signals analyzed using the Biokit datascope software. The system categorized into three categories (1) power supply unit (2) amplifier unit (3) data acquisition unit and (4) Opto-isolation unit.

3.4.1 Power Supply Unit

Power supply unit gives the 12V power to the EMG amplifier unit. For this purpose a 12V battery is used. Power supply is as shown in Fig.3.6.

Fig. 3.6 12V power supply

3.4.2 Amplifier Unit

Amplifier unit appropriately amplifies the SEMG signals grabbed from the surface of the skin with the help of disposable electrodes. EMG amplifier having specification:

- 3 wire patient cable
- Input impedance > 10 MΩ
- CMRR > 80 dB
- Gain= 10K max
- Frequency Response= 1Hz to 48 Hz

EMG amplifier is shown in Fig. 3.7 with 3 wire patient cable

Fig. 3.7 EMG amplifier with 3 wire patient cable

3.4.3 Data Acquisition Unit

Data acquisition unit acquires the amplified data and converts into a digital format, which is interfaced to the personal computer through a serial port (RS232). It is able to provide different sampling rate at different channel. Some other features of a data acquisition unit given below:

- RISC microcontroller based
- 4096 samples/Sec for single channel capture
- 1024 samples/Sec/channel for multi channels capture
- 8 channels
- Baud rate of 115200 bits/Sec.
- Optical isolation

Data acquisition unit is shown in Fig. 3.8.

Fig. 3.8 Eight channel data acquisition unit

3.4.4 Opto-Isolation Unit

The optical isolation unit provides isolation the Biokit Datascope system from the mains power, so that human safety is achieved. The optical isolation unit is shown in Fig. 3.9.

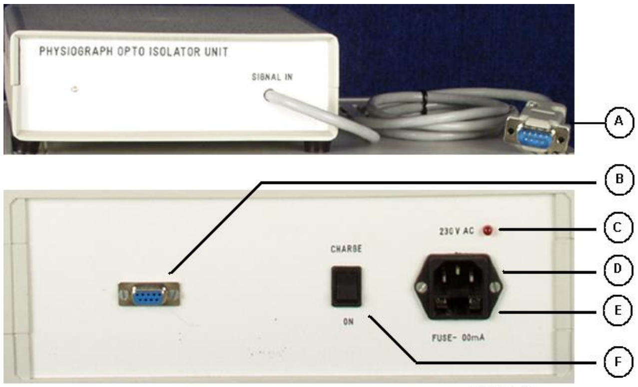

Fig. 3.9 Optical isolation unit

A: signal in serial male 9 pin cable interconnectivity to Datascope

B: serial interface connectivity to PC

C: power supply indicator

D: power input connector

E: fuse

F: ON/OFF switch

3.4.5 Sensor Connectivity

The datascope system accepts input from sensor amplifier through the 5 pin female connector of the datascope. The sensor is to be connected with the amplifier (as shown in fig. 3.10) for the proper working and the results of the system.

The 5 pin male connector shown below connects to the amplifier from the electrode

Fig. 3.10 Five pin male connector sensor

3.5 Fuzzy Approach to EMG Classification

Fuzzy logic systems are advantageous in biomedical signal processing and classification. Biomedical signals are not always strictly repeatable, and may sometimes even be contradictory. Fuzzy logic systems can tolerate contradiction in the data. Using the trainable fuzzy system, find the patterns in the data, which are not easily detected by other methods.

Fuzzy technology has the potential to deal with uncertainties that exist during arm movement. Hence, a rule based fuzzy system is used for EMG signal classification problem. In this section, the major components in a fuzzy system are discussed.

3.5.1 Fuzzy Logic System (FLS)

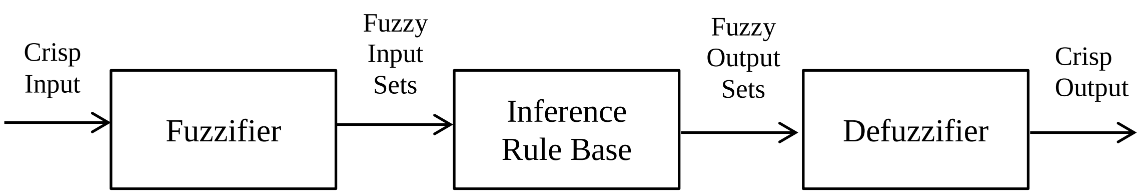

Fig. 3.11 Schematic representation of a fuzzy logic system (FLS)

A FLS shown in Fig. 3.11 has the following major components: a Fuzzifier, inference rule base and Defuzzifier. The inference engine maps each rule’s fuzzy input sets into each rule’s fuzzy output set. Rules are integral part of FLS. Each rule can be thought as a subsystem and it has one or many membership functions associated with it. The rules come into action only when input falls in the span of a particular fuzzy variable...

The fuzzy rules are nothing but a simple mapping from the inputs to the outputs and this mapping can be expressed quantitatively as $y = f(x)$. This kind of FLS is very common and widely used in many engineering applications of fuzzy logic, such as in FL controllers and signal processors. It is also stated as a fuzzy controller, fuzzy system, fuzzy expert system, or fuzzy model. There are a number of possibilities for a FLS. The design degrees of freedom that control the accuracy of a FLS are the number of inputs, the number of rules, and the number of fuzzy sets for each input variable.

The choice of membership function based on an estimate of the kind and quantity of noise present. This function is symmetric about its mean based on the assumption that noise effect is most likely to be equivalent on all points. Some of them are described below:

The equation of Gaussian membership function is shown in eq. 3.1.:

$$\mu(x) = exp\left[-\frac{1}{2}\left(\frac{x_i - c_i}{\sigma_i}\right)^2\right] \tag{3.1}$$

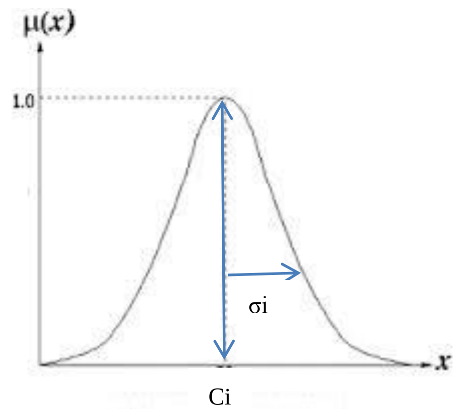

Fig. 3.12 Gaussian membership function

The equation of triangular membership function is shown in eq. 3.2.:

$$\mu(x) = \begin{Bmatrix} max\left\{0, 1 + \frac{x_i - c_i}{0.5\sigma_i}\right\} & if\ x_i \leq c_i \\ max\left\{0,1 + \frac{c_i - x_i}{0.5\sigma_i}\right\} & otherwise \end{Bmatrix} \tag{3.2}$$

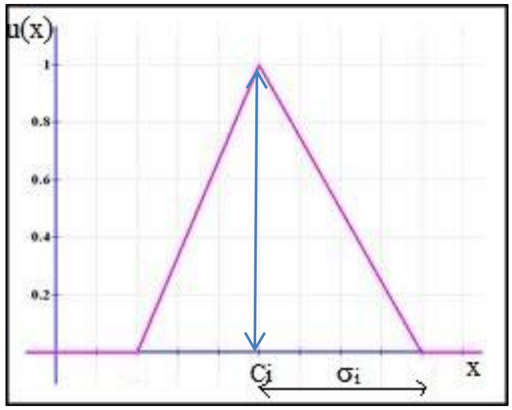

Fig. 3.13 Triangular membership function

where x_i is the i^{th} input variable, c_i is the i^{th} center of the membership function (i.e., where the membership function achieves a maximum value), a standard deviations value that represents the spread of these sets. Larger values of the spread for these membership functions imply that more noise is exist in the data.

Finally, a FLS contains many design parameters whose values must be set by user before FLS.is designed. There are many ways to do this, and all these methods make use of a set of data, usually called the training set. This set consists of input-output pairs for the FLS.

3.5.2 Fuzzy Rules for EMG Classification

In order to establish the fuzzy rules for a fuzzy logic system a certain number of input-output training pairs are chosen. The next step is to convert the training dataset into a set of fuzzy rules (IF-THEN, IF-THEN-ELSE, etc.). The simplest representation is IF-THEN approach, which is applied in the present work.

If the N crisp inputs are represented as x^1, x^2,…, x^N and the crisp output variables are represented as y^1, y^2,…,y^N, then the possible training pairs are the (x^1, y^1), (x^2, y^2),…, (x^N, y^N). Input and output are to be related with IF-THEN rules.

The design methods adopted usually determine the values of the parameters in the antecedent and consequent membership functions based on the training dataset. The maximum number of rules that will represent the system is divided on the basis of the number of training pairs. Tuning is a process that determines an optimal system that provides the best fit to the input-output pairs. Tuning basically reduces the number of rules.

The following are some methods to extract rules from the numerical training data:

1. The centers of the fuzzy sets in the antecedents and consequents of the rules are obtained directly from the training data.
2. Assume fuzzy sets for the antecedents and consequents ahead of time and then relate the data with these fuzzy sets.
3. The FLS is first designed and then all its design parameters are optimized using the training data.

The extraction of rules from the data is explained in detail below. A rule is of the form:

Rule1: IF x_1 is F_1 and x_2 is F_2 …………… and x_p is F_p, THEN y is G

Here F_1, F_2, ……, Fp fuzzy sets whose membership function is centered at the measured value *of* x_1, x_2, …., and x_p.

In this method, the centers of the antecedent and consequent membership function are completely determined by the training data. In this method, the numerical training data are used just one time to obtain all the rules.

3.6 Defuzzyfication

Defuzzification is the process of converting the degrees of membership of fuzzy output variables within their terms in to crisp numerical values. In the fuzzy system, the methods to perform defuzzyfication are summarized as:

- Center of Area (CoA)
- Modified center of Area
- Center of Sum (CoS)
- Center of Maximum (CoM)

In presented work center of area (CoA) method is used for defuzzyfication. tn the center of the area defuzzyfication method, the fuzzy system first calculates the area under the scaled membership function and within the range of the output variable. The fuzzy system is used the Eq. 3.3 to calculate the geometric center of this area.

$$CoA = \frac{\int_{Xmin}^{Xmax} f(x) * x \, dx}{\int_{Xmin}^{Xmax} f(x) \, dx} \qquad 3.3$$

Where

CoA = Center of Area

x is the value of variable

x_{min} and x_{max} range of the fuzzy sets

CHAPTER 4

METHODOLOGY

SEMG signal is obtained from the surface of the body by using disposable electrodes. For the acquisition of SEMG signal BIOKIT Datascope system is used. BIOKIT system having various parts like a rechargeable battery, EMG amplifier, analog to digital converter, sensor, connecting cords and personal computers. The block diagram of acquisition of EMG signal is shown in Fig. 4.1

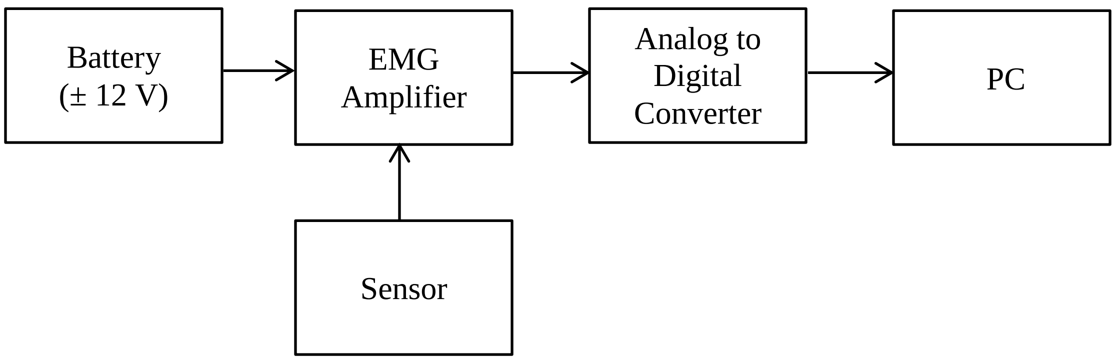

Fig. 4.1 Block diagram of EMG acquisition system

EMG signal is recorded using sensor of EMG amplifier from disposable electrode. EMG signal is recorded about 4096 samples per second for time window 4 second of data scope in the workspace. EMG signal saved in PC using BIOKIT system using Datascope software. A file *.BIO (file format) is generated by the system, which can be used by PC for analysis purpose.

Further analysis and feature extraction of SEMG signals is done by using LabVIEW. LabVIEW, short for Laboratory Virtual Instrument Engineering Workbench, is a programming environment in which you create programs using a graphical notation (connecting functional nodes via wires through which data flows). A program is made for reading the EMG signal which recorded by BIOKIT system. Time domain features of EMG signal like V_{rms}, Integrated EMG (IEMG), zero crossing rate (ZCR) and mean absolute value (MAV) are calculated using LabVIEW. The block diagram of the system is shown in Fig. 4.2

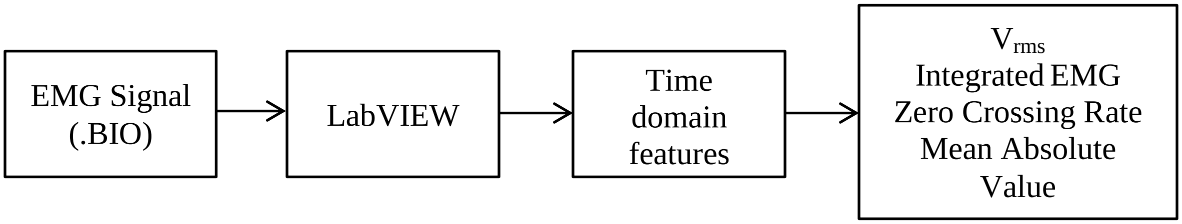

Fig. 4.2 Block diagram of feature extraction using LabVIEW

The complete process is discussed in the preceding step as:

Firstly, the Biokit setup prepared for acquiring the EMG signals from the subjects for two different cases (1) grip the different weights and (2) lift the different weights from two positions of the hand.

Fig. 4.3 Setup for grasp movement

Fig. 4.4 Setup for lift movement

The two positions considered for acquisition of EMG are (1) Flexor carpum ulnaris (below elbow) for grip the different weights and (2) biceps brachhi (between elbow and shoulder) for lift the different weights. These two EMG signals acquired from single channel at a time.

After acquiring of the EMG signal from Biokit datascope to analysis the data, a program is developed in LabVIEW for acquiring to LabVIEW environment. Block diagram of program is shown in Fig. 4.5

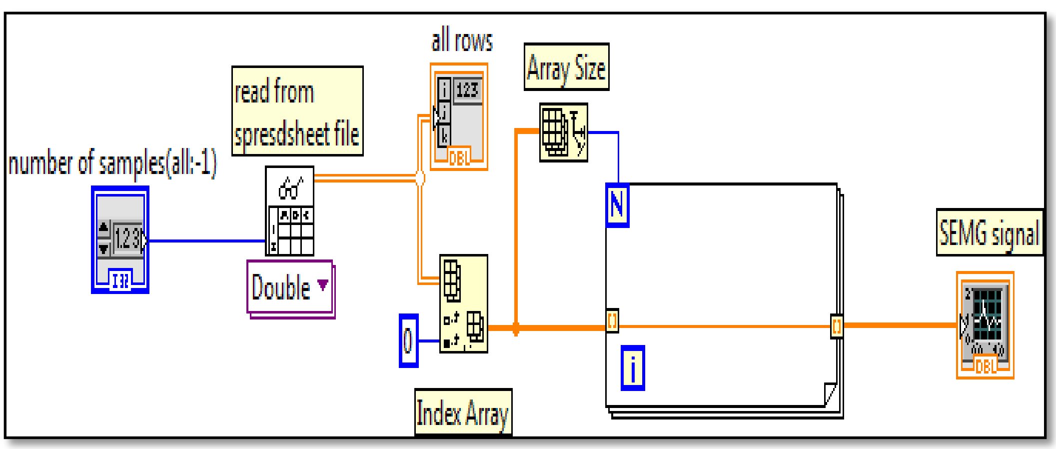

Fig. 4.5 (a) Block diagram of program to acquiring the signal in LabVIEW

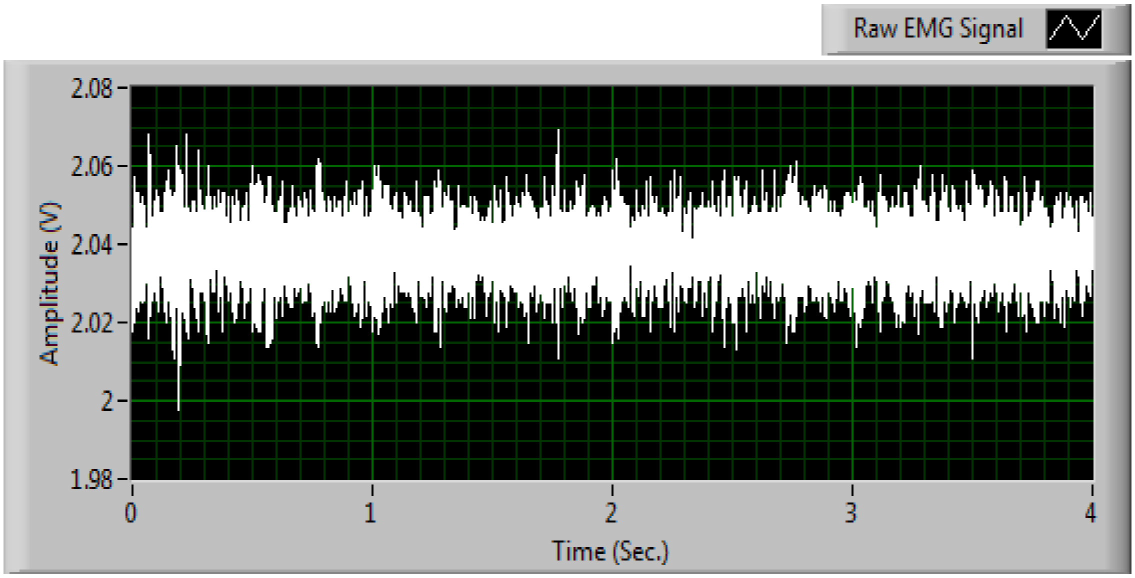

Fig. 4.5 (b) Front panel of program to acquiring the signal in LabVIEW

Once the signal is acquired in LabVIEW environment, next step is to condition the signal for feature extraction purpose.

4.1 Base Line Shifting

The human being produces a static current, which interferes while acquiring SEMG signals. Due to this, the SEMG signal shifts to upper side of the base line. This defect occurs due to the tension of the muscle, body movement and environmental noise. So the base line of SEMG is shifted to zero line. For this purpose a Butterworth band pass filter is used which is a combination of low pass filter and high pass filter. Here lower cutoff frequency is set to be 10 Hz and higher cutoff frequency is set to be 500 Hz. Most of the EMG signal contents lie in this region. A high pass filter is used to attenuate DC offset noise voltage and low pass filter is used for removing environmental noise. A program is developed in LabVIEW for baseline shifting.

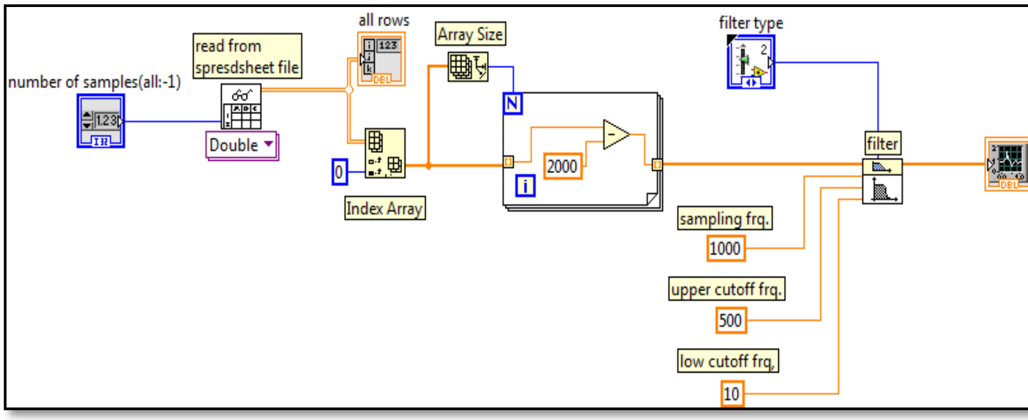

Fig. 4.6 (a) Block diagram of program for baseline shifting

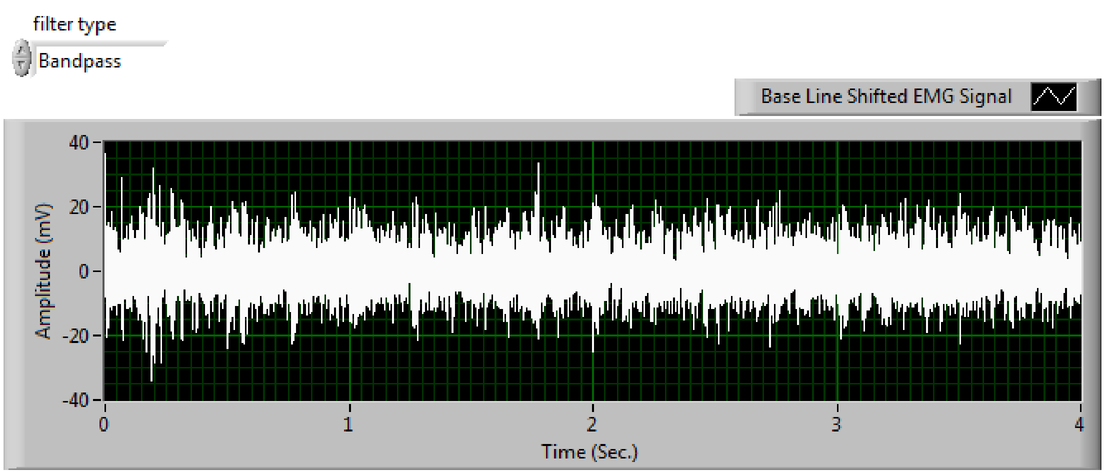

Fig. 4.6 (b) Front panel of program for baseline shifted at zero

When the baseline is shifted to zero, the various features are extracted from the EMG signal for analysis and classification.

4.2 Feature Extraction & Calculation

Each member of the raw data set contains a single channel. Each set of raw data consists of 30 samples and each sample contains 3 different motion of grasp and lift with different weights of the EMG signal. Each sample is recorded for 4 sec of time window. Thus 180 raw EMG data elements are available that best distinguish one class of grasps and lift of different weights from another. This process is called feature extraction and has the greatest impact on the ability of a classifier to successfully associate the raw data with its class. There are several approaches to feature extraction specifically relevant to EMG data. (1) Temporal and (2) spectral. In the presented work, only temporal feature are selected. 180 EMG recordings are used in this work. The feature extracted are summarized as fallows

4.2.1 Root Mean Square Value (V_{rms})

The root mean square (abbreviated RMS or 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 positive and negative. The RMS value of a set of values (or a continuous-time waveform) 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).

The Eq. 4.1 gives the RMS value for ‘n’ samples. Figure 4.7 (a) shows the block diagram of program to calculate RMS value. Figure 4.7 (b) shows the front panel of program to calculate RMS value. The RMS value is given by:

$$V_{rms} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} x_n^2} \tag{4.1}$$

where,

V_{rms} – the root mean square value

Xn – value of samples

n- no. of samples

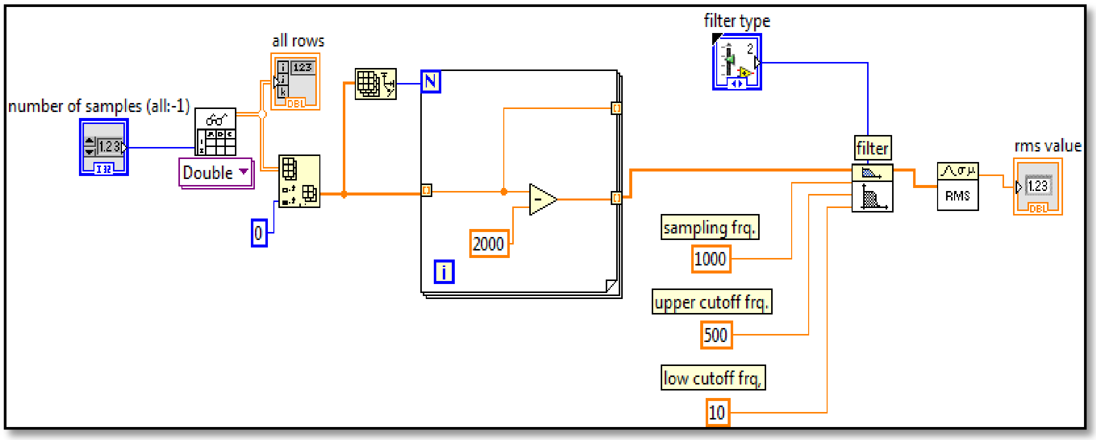

Fig. 4.7 (a) Block diagram of program to calculate RMS

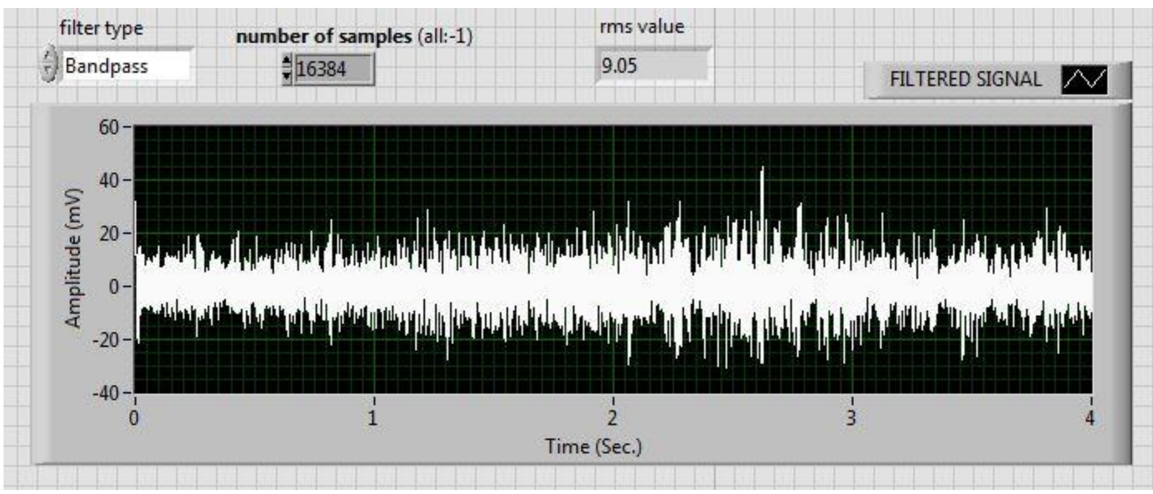

Fig. 4.7 (b) Front panel of program to calculate RMS

4.2.2 Mean Absolute Value (MAV)

Mean Absolute Value (MAV) is similar to average rectified value (ARV). It can be calculated using the moving average of full-wave rectified EMG. In other words, it is calculated by taking the average of the absolute value of sEMG signal. It is an easy way for detection of muscle contraction levels and it is a popular feature used in the myoelectric control application.

The Eq. 4.2 gives the mean absolute value for '*n*' samples. Figure 4.8 (a) shows the block diagram of program to calculate mean absolute value. Figure 4.8 (b) shows the front panel of program to calculate mean absolute value. The mean absolute value is given by:

$$M = MAV = \frac{1}{N}\sum_{n=1}^{N}|x_n| \tag{4.2}$$

where

x_n= EMG signal in a segment

N= Length of the EMG signal

M= MAV= Mean Absolute Value

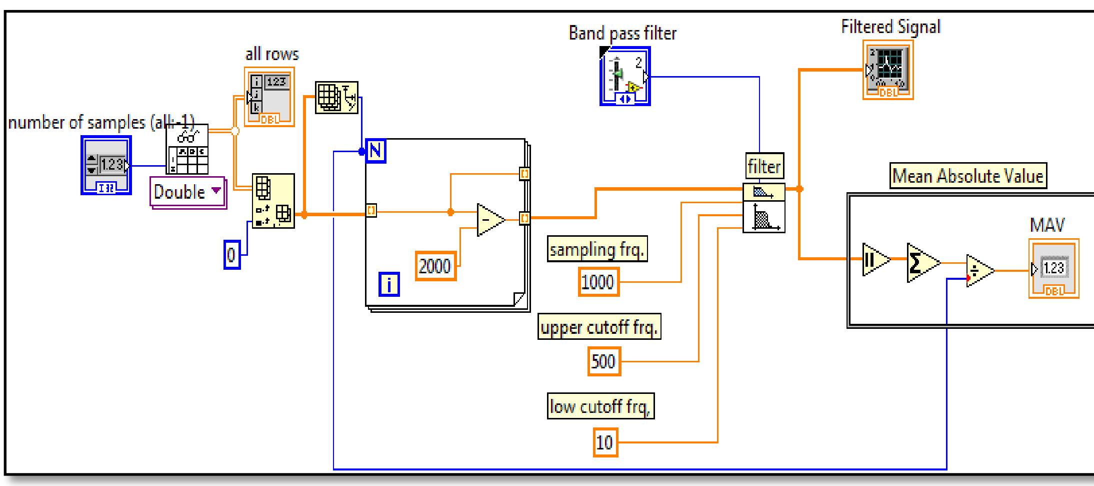

Fig. 4.8 (a) Block diagram of program to calculate mean absolute value

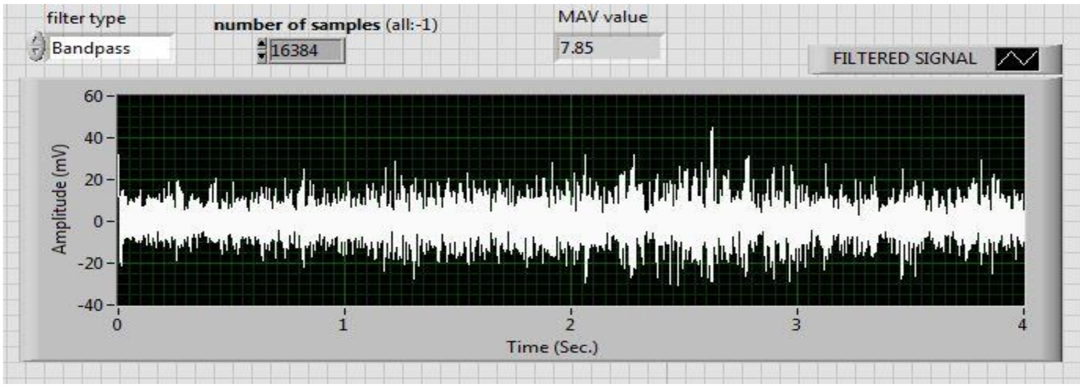

Fig. 4.8 (b) Front panel of program to calculate mean absolute value

4.2.3 Integrated EMG (IEMG)

Integrated EMG (IEMG) is calculated as the summation of the absolute values of the sEMG signal amplitude. Generally, IEMG is used as an onset index to detect the muscle activity that used to oncoming the control command of assistive control device. It is related to the sEMG signal sequence firing point.

The eq. 4.3 gives the integrated EMG value for ‘n’ samples. Figure 4.9 (a) shows the block diagram of program to calculate IEMG value. Figure 4.9 (b) shows the front panel of program to calculate IEMG value. The IEMG value is given by:

$$IEMG = \sum_{n=1}^{N} |x_n| \tag{4.3}$$

where

N= Length of the EMG signal

X_n= SEMG signal in segment

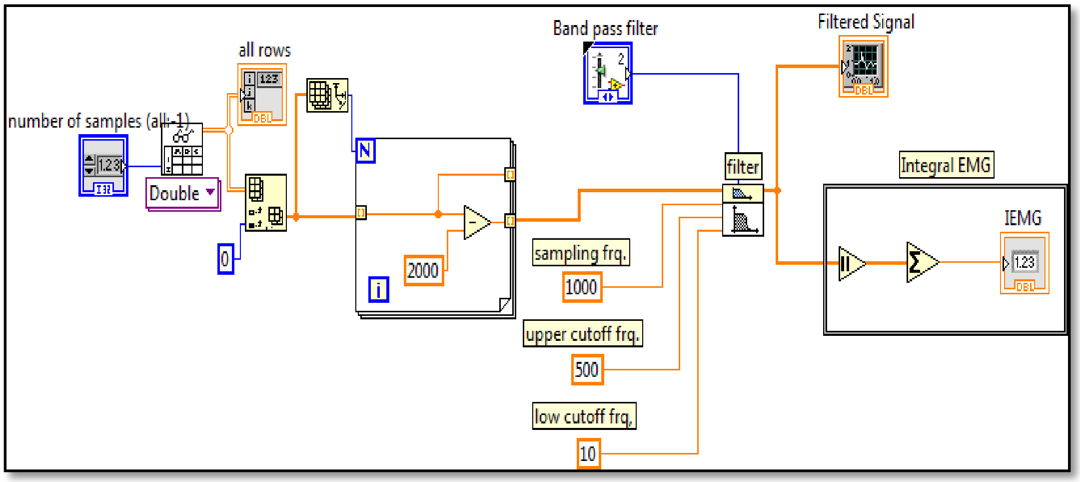

Fig. 4.9 (a) Block diagram of program to calculate integrated EMG value

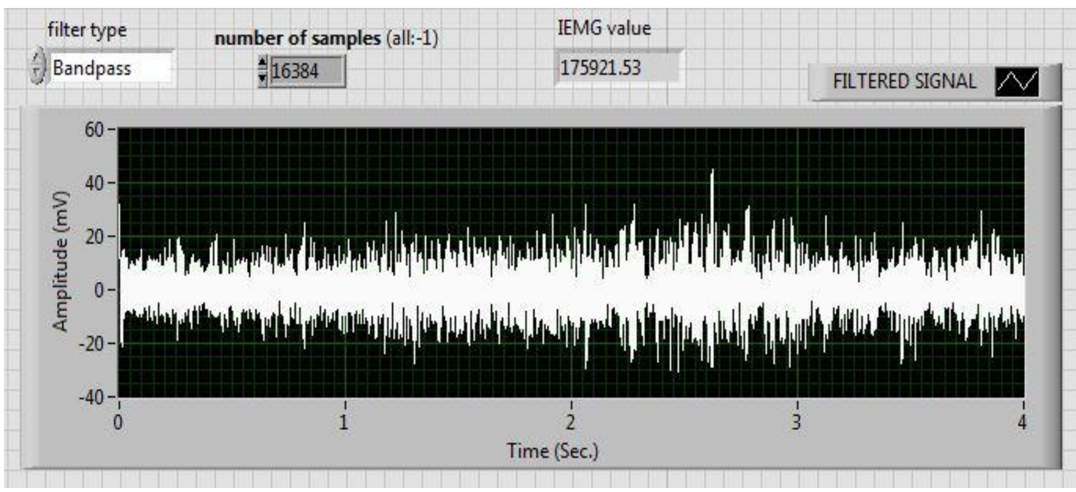

Fig. 4.9 (b) Front panel of program to calculate integrated EMG value

4.2.4 Zero Crossing Rate (ZCR)

Zero-crossing rate (ZCR) expresses the number of times a signal crosses the axis of abscissas. The random temporal fluctuations of the EMG signal may serve as distinguishable feature. Hence, the ZCR is also considered as a distinguishable feature to comment on the detection of diseases.

The eq. 4.4 gives the zero crossing rate of EMG signal for 'n' samples. Fig. 4.10 (a) shows the block diagram of program to calculate zero crossing rate. Fig. 4.10 (b) shows the front panel of program to calculate zero crossing rate. The zero crossing rate is given by:

$$ZCR = \frac{1}{2N}\left\{\sum_{k=1}^{k=N-1} |sgn[x(k)] - sgn[x(k-1)]|\right\} \qquad (4.4)$$

where

$$sgn[x] = \begin{cases} 1, & x \geq 0 \\ -1, & x \leq 0 \end{cases}$$

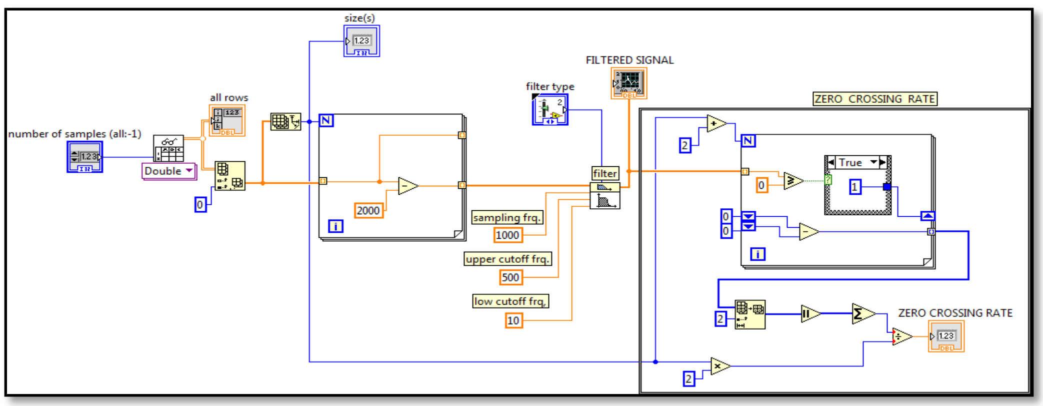

Fig. 4.10 (a) Block diagram of program to calculate zero crossing rate

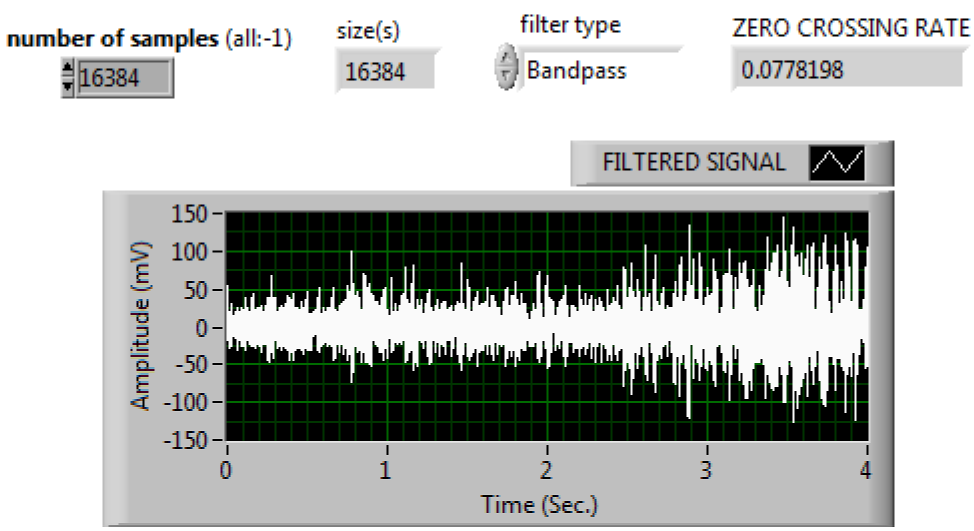

Fig. 4.10 (b) Front panel of the program to calculate zero crossing rate

Pattern recognition, in simple terms means the classification of a dataset based on the features that represent the data. These features are obtained using feature selection (extracting features that characterize the given dataset).

4.3 Design of Fuzzy Classifier

There are many ways to classify the EMG signals. In this work, the rule-based approach is applied for the EMG signal classification. For this purpose, a fuzzy logic toolkit of LabVIEW is used and a classifier is designed with the help of this toolkit.

The fuzzy system designer is used for the classifier designing in LabVIEW. The fuzzy system designer is opened from the front panel of the LabVIEW. The fuzzy system designer has three components (1) Variables, (2) Rules, (3) Test System

Variables of fuzzy system designer have input variables and output variables. For input variables, three features of EMG signal are selected. These features are mean absolute value (MAV), zero crossing rate and integrated EMG (IEMG). Output variable is weight. The main window of fuzzy system designer is as shown in Fig. 4.11

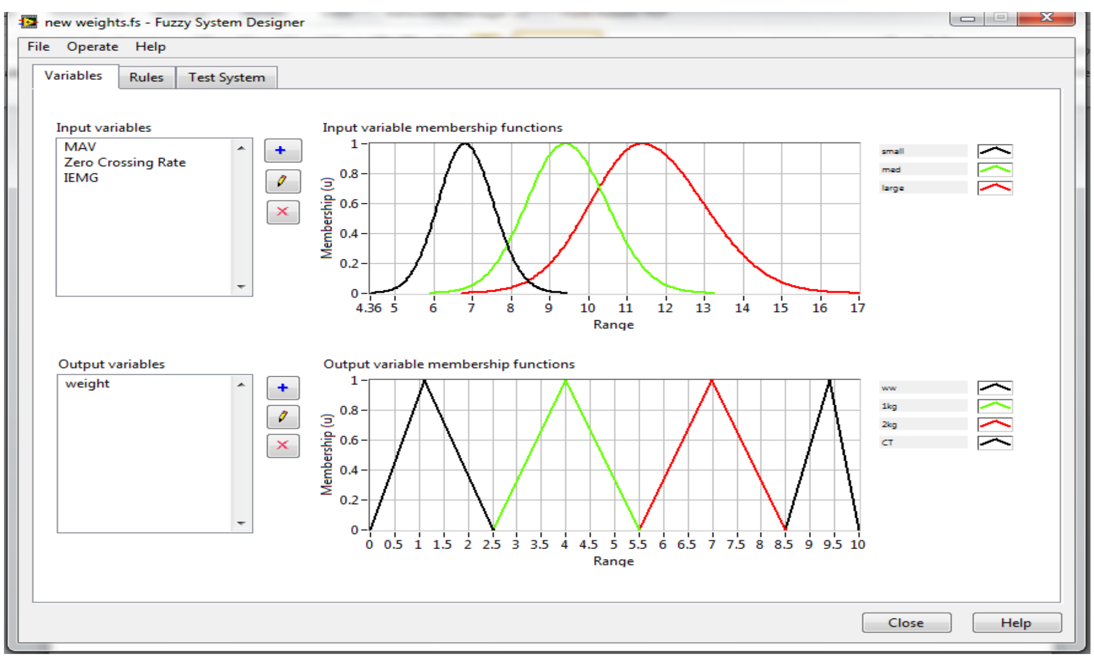

Fig. 4.11 Fuzzy system designer in LabVIEW

4.3.1 Classifier for Grasps Movement

For designing of membership function of input variables, Gaussian function is used and each input variable has three fuzzy sets small, medium and large. The values of these fuzzy sets are listed in Figure 4.12, 4.13, 4.14 below.

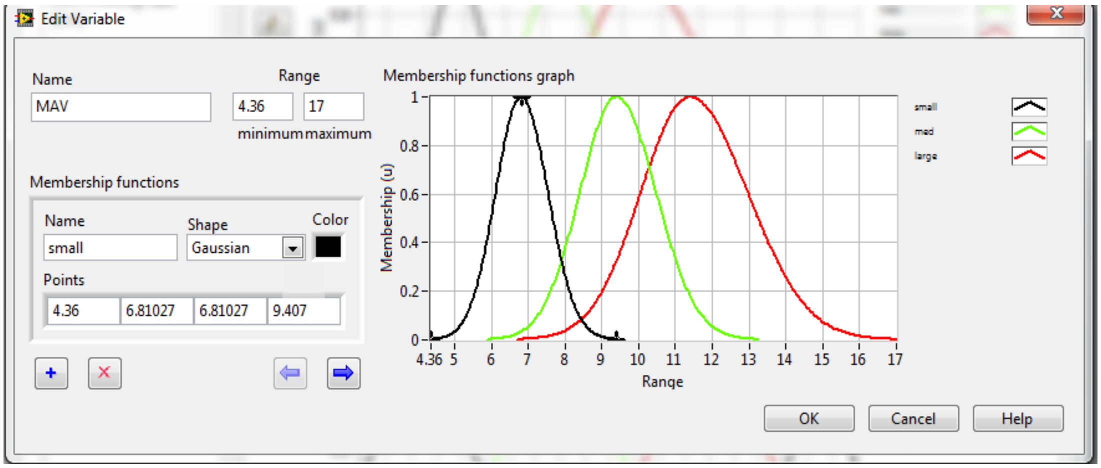

Fig. 4.12 Membership function values of mean absolute

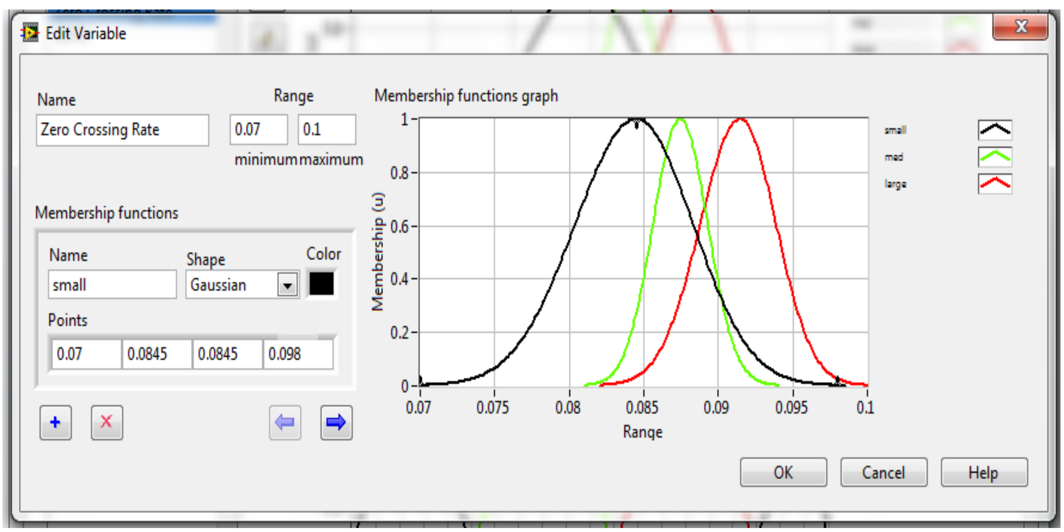

Fig. 4.13 Membership function value of zero crossing rate

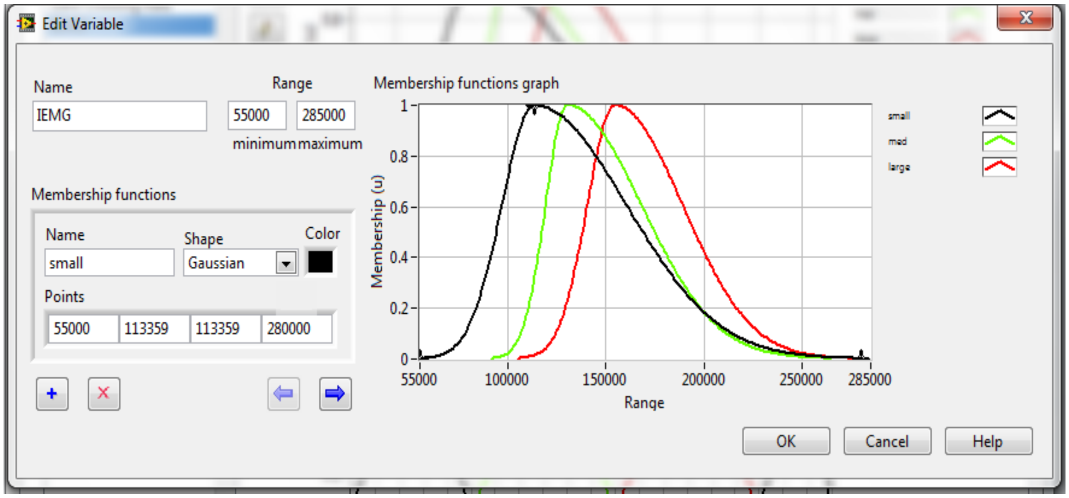

Fig. 4.14 Membership function values of integrated EMG

For designing of membership function of output variables, Triangular function is used and output variable has four fuzzy sets or four classes that are ww (without weight), 1 Kg., 2 Kg and CT (Continue Testing). Value of these fuzzy sets is shown in Figures below.

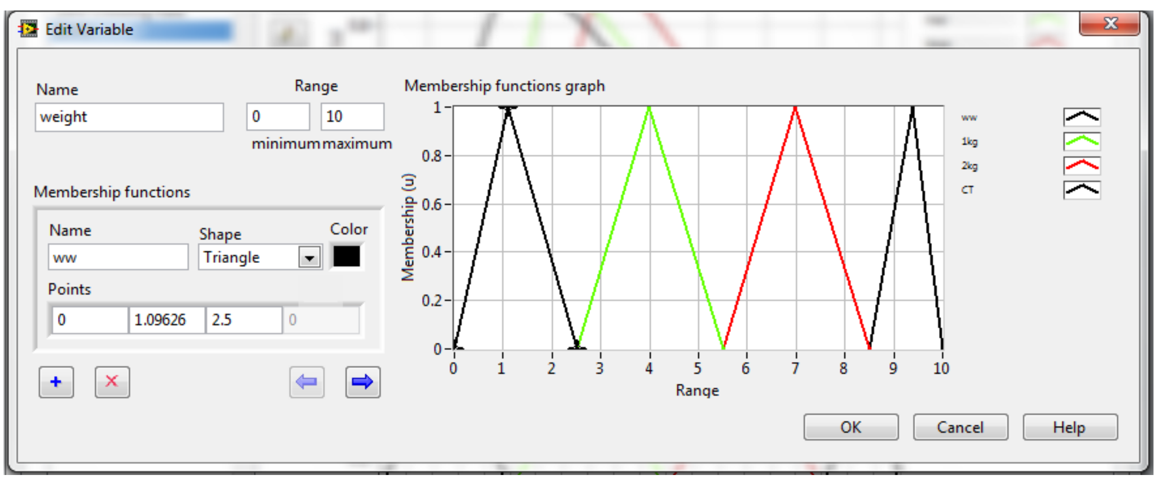

Fig. 4.15 Membership function values of output weights

Once the fuzzy sets of input variables are prepared with the help of available data, rules are made using relationship of input and output variables. These rules are in the form of IF-THEN and rules are listed in Table 4.1.

Table 4.1 Rules of grasp movement for different weights:							
Rule	**MAV (input)**		**Zero Crossing Rate(input)**		**IEMG (input)**		**Weights (output)**
1	small	AND	small	AND	small	THEN	CT
2	small	AND	small	AND	med	THEN	CT
3	small	AND	small	AND	large	THEN	CT
4	small	AND	med	AND	small	THEN	CT
5	small	AND	med	AND	med	THEN	CT
6	small	AND	med	AND	large	THEN	CT
7	small	AND	large	AND	small	THEN	ww
8	small	AND	large	AND	med	THEN	CT
9	small	AND	large	AND	large	THEN	CT
10	med	AND	small	AND	small	THEN	CT
11	med	AND	small	AND	med	THEN	CT
12	med	AND	small	AND	large	THEN	CT
13	med	AND	med	AND	small	THEN	CT
14	med	AND	med	AND	med	THEN	1Kg
15	med	AND	med	AND	large	THEN	CT
16	med	AND	large	AND	small	THEN	CT
17	med	AND	large	AND	med	THEN	CT
18	med	AND	large	AND	large	THEN	CT
19	large	AND	small	AND	small	THEN	CT
20	large	AND	small	AND	med	THEN	CT
21	large	AND	small	AND	large	THEN	2Kg
22	large	AND	med	AND	small	THEN	CT
23	large	AND	med	AND	med	THEN	CT
24	large	AND	med	AND	large	THEN	CT
25	large	AND	large	AND	small	THEN	CT
26	large	AND	large	AND	med	THEN	CT
27	large	AND	large	AND	large	THEN	CT

The test system is used for checking the classifier outputs with respect to the given value of inputs. Test system have input/output relationship graph which shows the value of output at given inputs and gives the information about invoked rule and it's weights in fuzzy classifier. The test system is shown in Fig. 4.16.

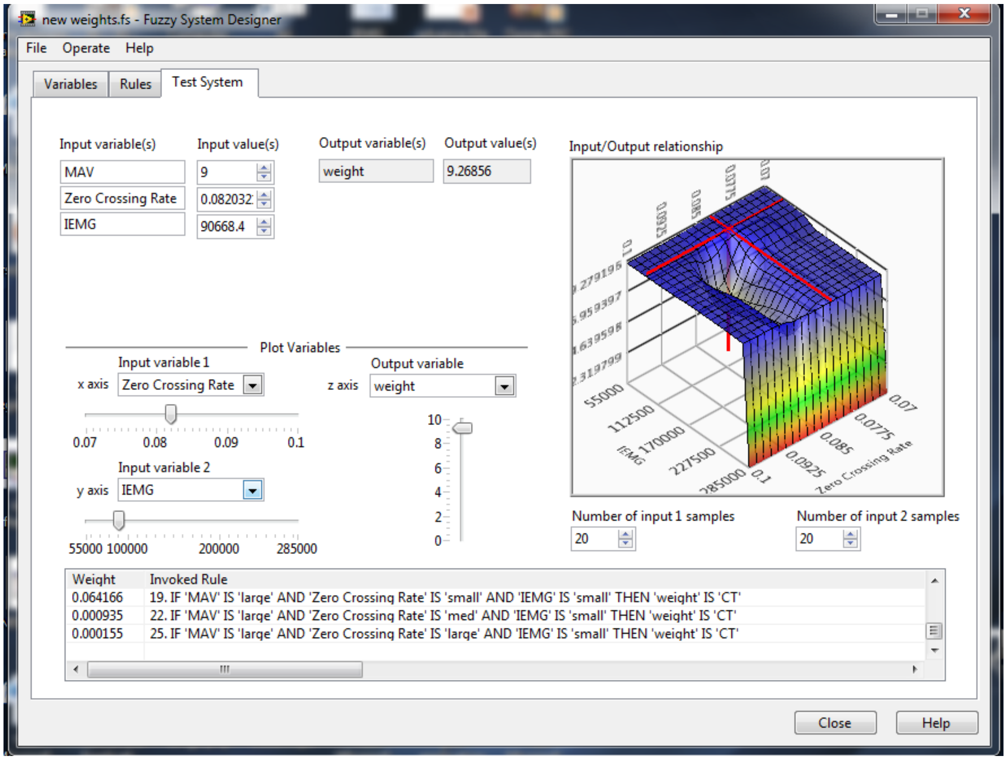

Fig. 4.16 Test system of fuzzy system designer for grasp movement

4.3.2 Classifier for Lift Movement

For designing of membership function of input variables, Gaussian function is used and each input variable has three fuzzy sets small, medium and large. The ranges of fuzzy sets are defined with the help of given data. Values of these fuzzy sets are listed in Figure 4.17, 4.18, 4.19 below.

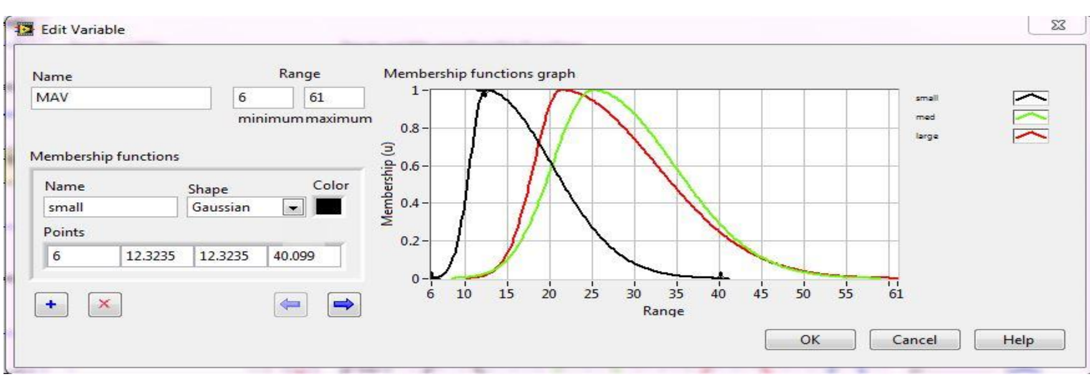

Fig. 4.17 Membership function values of the mean absolute value of lift movement

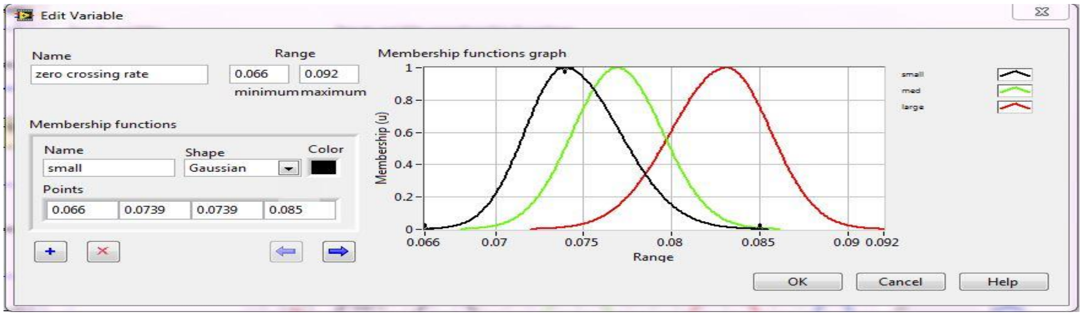

Fig. 4.18 Membership function values of zero crossing rate for lift movement

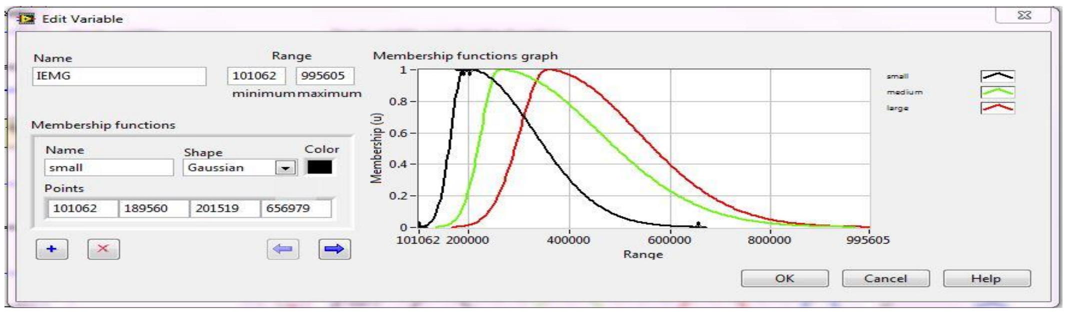

Fig. 4.19 Membership function values of the integrated EMG value of lift movement

For designing of membership function of output variables, Triangular function is used and output variable has four fuzzy sets or four classes that are WW (without weight), 1Kg., 2Kg and CT (Continue Testing). Value of these fuzzy sets is shown in Figures 4.20 below.

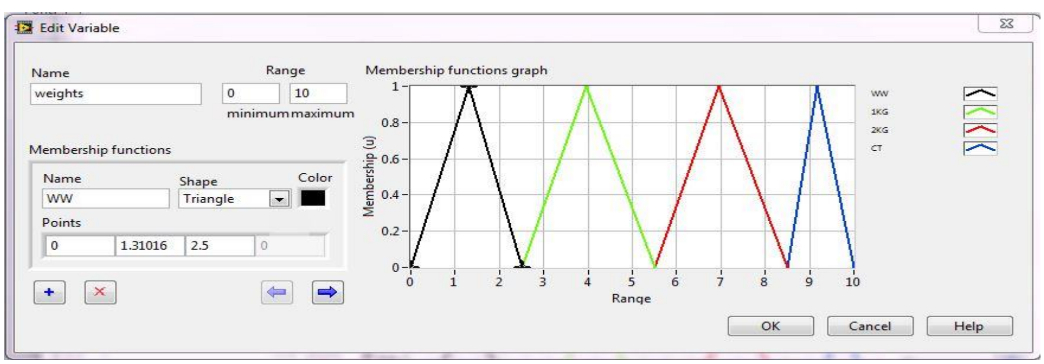

Fig.4.20 Membership function values of output weights

Once the fuzzy sets of input variables are prepared with the help of available data, rules are made using relationship of input and output variables. These rules are in the form of IF-THEN and rules are listed in Table 4.1.

Table 4.2 Rules of lift movement for different weights:

Rule	**Zero Crossing Rate (input)**		**MAV (input)**		**IEMG (input)**		**Weights (output)**
1	small	AND	small	AND	small	THEN	CT
2	small	AND	small	AND	med	THEN	CT
3	small	AND	small	AND	large	THEN	CT
4	small	AND	med	AND	small	THEN	CT
5	small	AND	med	AND	med	THEN	CT
6	small	AND	med	AND	large	THEN	CT
7	small	AND	large	AND	small	THEN	CT
8	small	AND	large	AND	med	THEN	CT
9	small	AND	large	AND	large	THEN	2 Kg
10	med	AND	small	AND	small	THEN	CT
11	med	AND	small	AND	med	THEN	CT
12	med	AND	small	AND	large	THEN	CT
13	med	AND	med	AND	small	THEN	CT
14	med	AND	med	AND	med	THEN	1Kg
15	med	AND	med	AND	large	THEN	CT
16	med	AND	large	AND	small	THEN	CT
17	med	AND	large	AND	med	THEN	CT
18	med	AND	large	AND	large	THEN	CT
19	large	AND	small	AND	small	THEN	WW
20	large	AND	small	AND	med	THEN	CT
21	large	AND	small	AND	large	THEN	CT
22	large	AND	med	AND	small	THEN	CT
23	large	AND	med	AND	med	THEN	CT
24	large	AND	med	AND	large	THEN	CT
25	large	AND	large	AND	small	THEN	CT
26	large	AND	large	AND	med	THEN	CT
27	large	AND	large	AND	large	THEN	CT

Test system is used for checking the classifier outputs with respect to the given value of inputs. Test system have input/output relationship graph which shows the value of output at given inputs and gives the information about invoked rule and it's weights in fuzzy classifier. Test system is shown in Fig. 4.21.

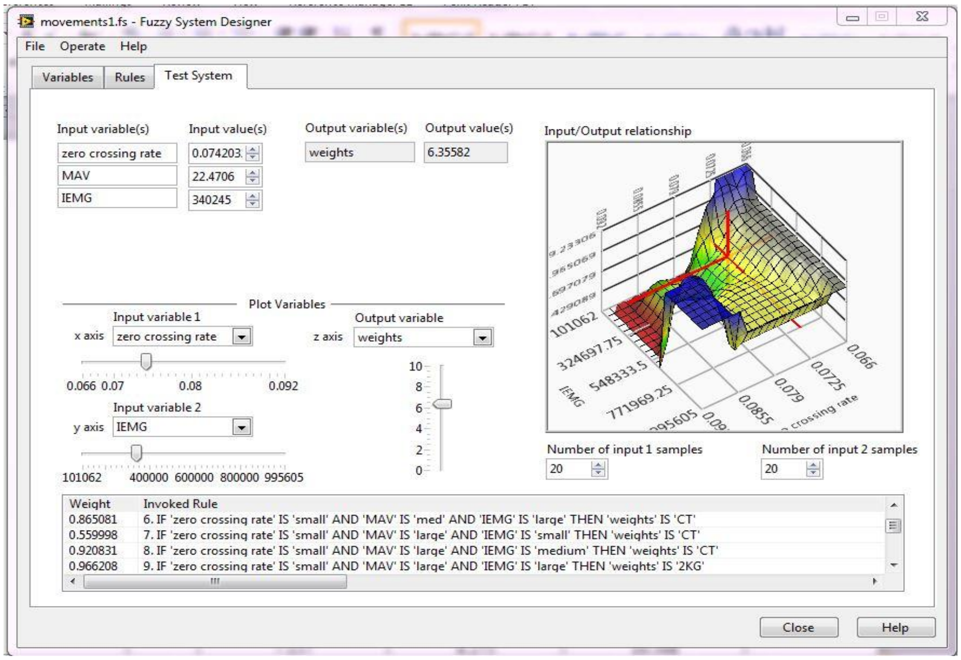

Fig. 4.21 Test system of fuzzy system designer for lift movement

After designed the classifiers for grip movement and lift movement,a program to classify the subjects is developed using LabVIEW. The program acquires the EMG signal and extractes the feature (mean absolute value, zero crossing rate and integrated EMG). These extracted values are input to the fuzzy classifier. Corresponding to given inputs, classifier gives the output that which weights are for which signal.

Block diagram of program that classified the EMG signal is shown in Fig. 4.22(a) and front panel of classification program is shown in Fig. 4.22(b).

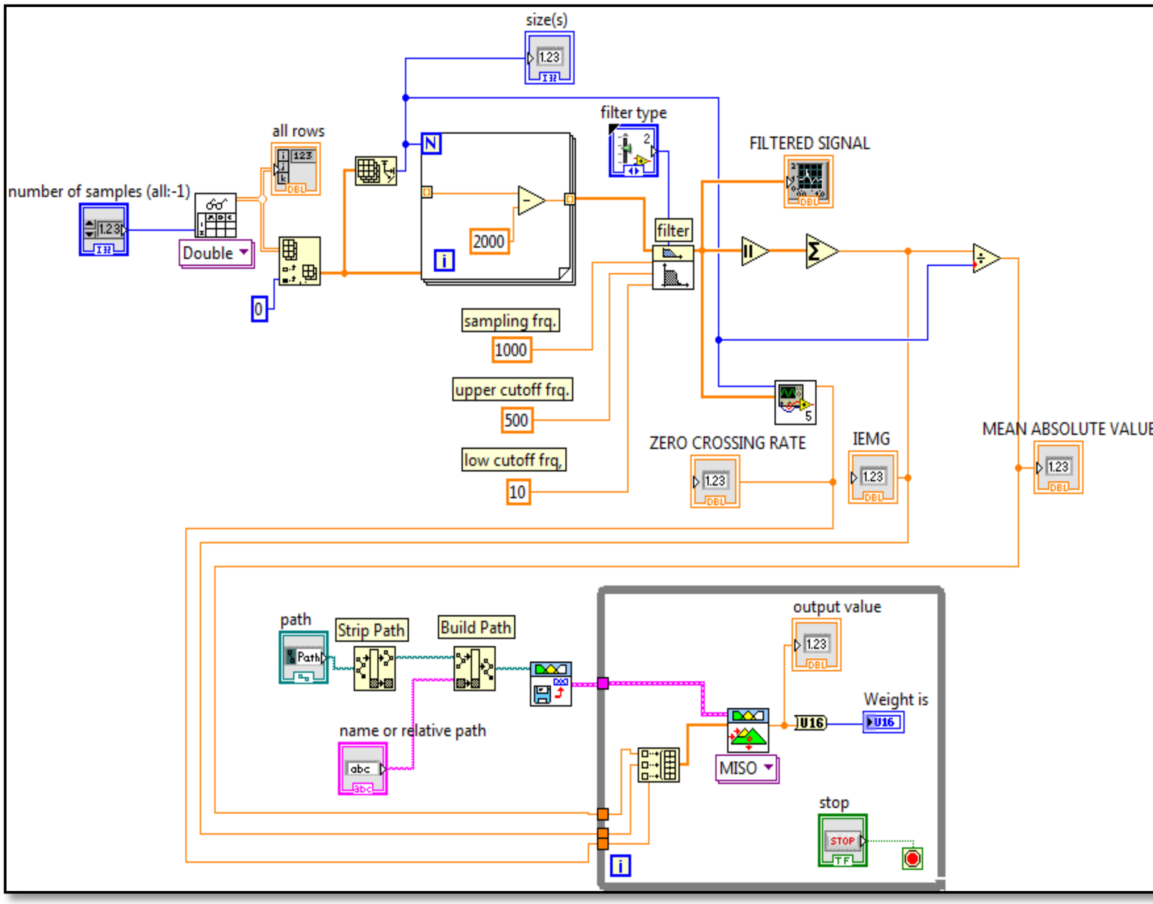

Fig.4.22 (a) Block diagram of program to classify EMG signal

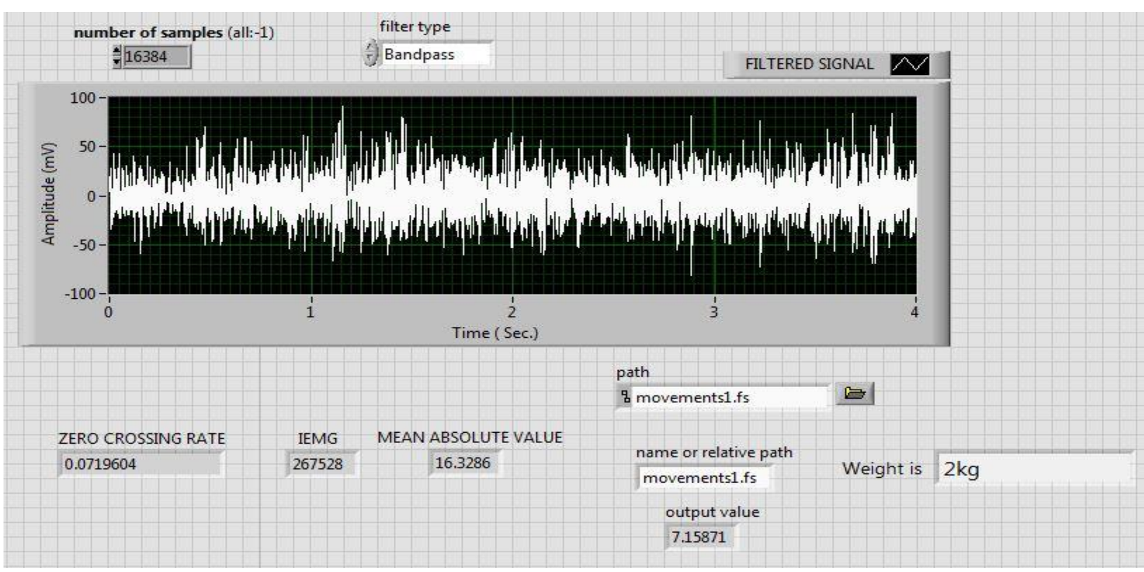

Fig. 4.22 (b) Front panel of program to classify EMG signal

CHAPTER 5
RESULTS AND DISCUSSIONS

The SEMG signal was acquired by using Biokit system and DataScope software. The features, rms value of EMG (V_{rms}), mean absolute value (MAV), integrated EMG (IEMG) and zero crossing rate (ZCR) were extracted from 30 subjects (12 female and 18 male) using LabVIEW given in Appendix A.

5.1 RMS Value of EMG (V_{rms})

EMG signal rms value is used to calculate constant force and non-fatiguing contraction. From the Fig. 5.1(a), 5.1(b) it is analyzed that the EMG signals of rest muscles having small rms values as compared to the active or movement muscles for a single subject. Small and large variations are observed, when subjects grasp and lift the different weights.

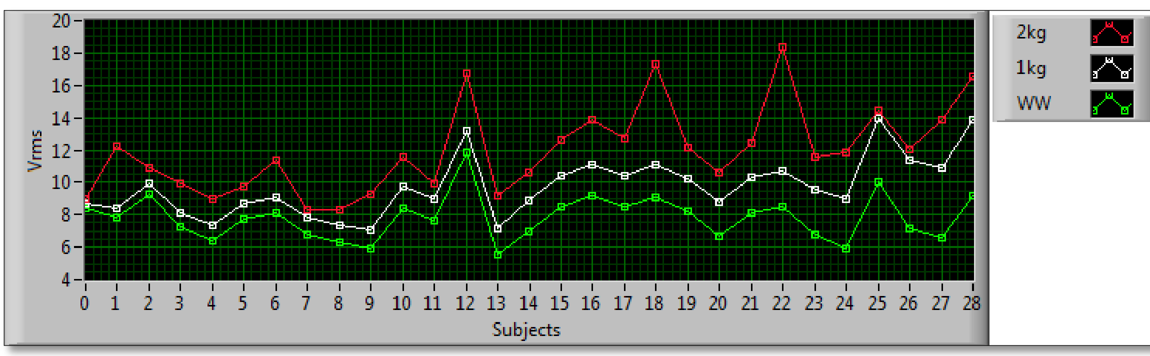

Fig. 5.1(a) Root mean square values for grasp movement using different weights

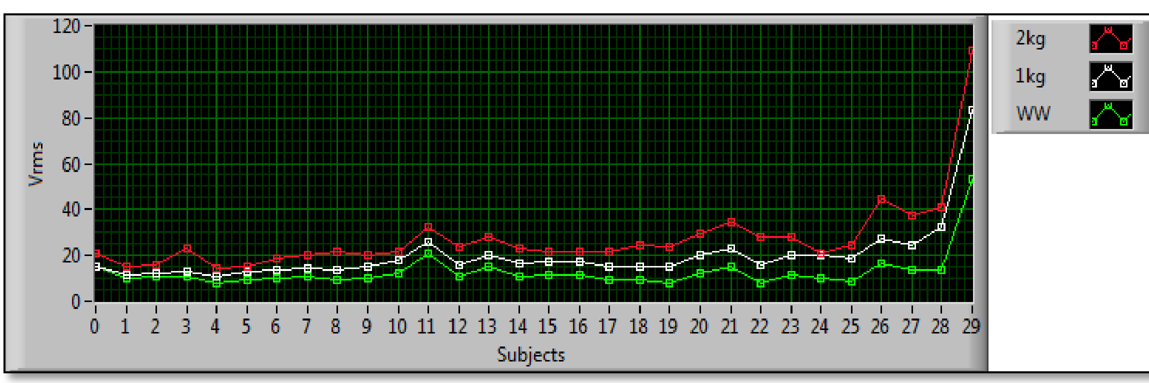

Fig. 5.1(b) Root mean square value for lift movement using different weights

5.2 Mean Absolute Value of EMG

The mean absolute value of EMG signal is used to find the contraction level of the muscles. From Fig. 5.2(a), 5.2(b) it is analyzed that contraction of muscles is more during lift and grasp the heavy weight as compared to the light weight. Mean absolute value is the moving average of full wave rectified of EMG signal. It is seen that as the weight increases, the mean absolute value of EMG signal also increased.

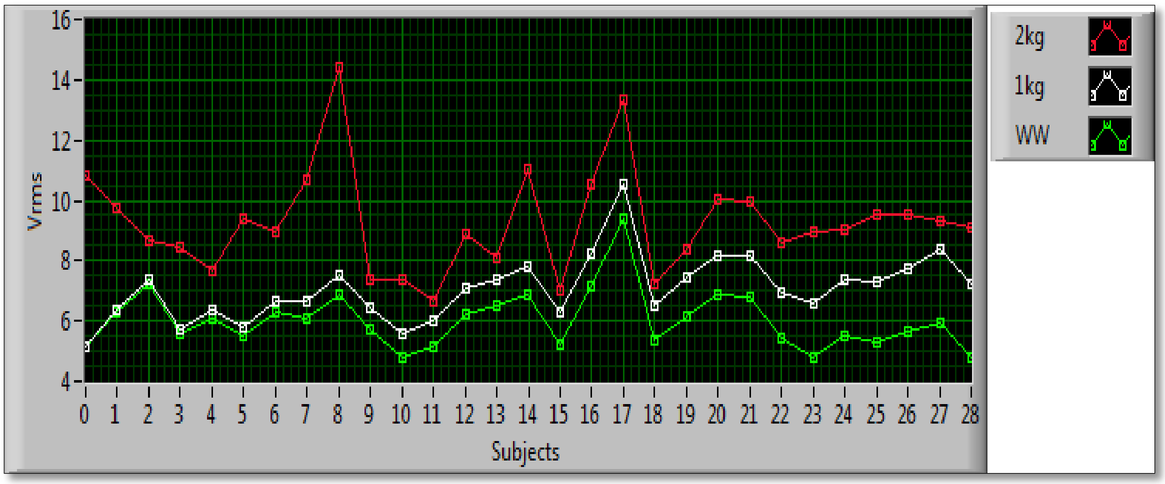

Fig. 5.2(a) Mean absolute values for grasp movement using different weights

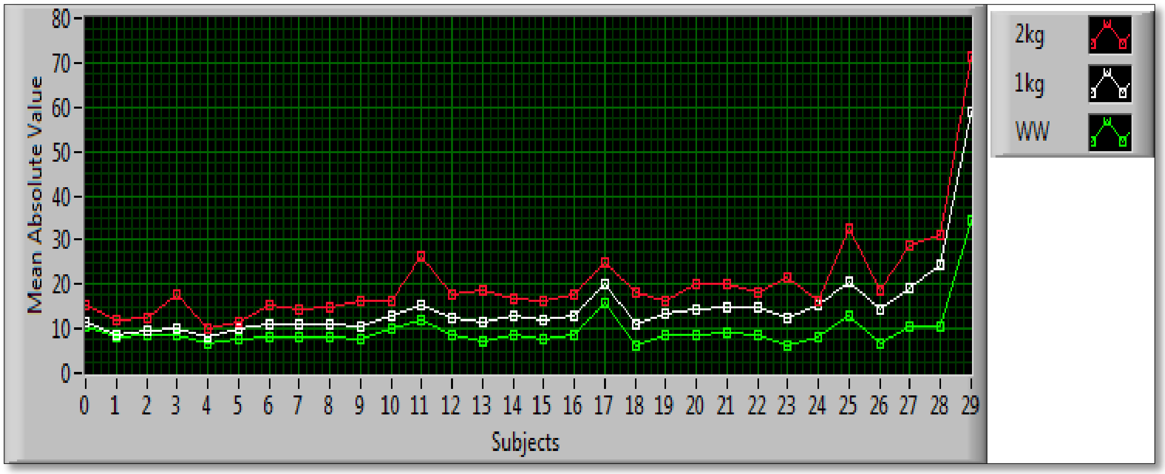

Fig. 5.2(b) Mean absolute values for lift movement using different weights

5.3 Zero Crossing Rate of EMG

Zero crossing rate of EMG signal shows at which rate signal crosses the x-axis. From Fig.5.3 (a), 5.3(b) it is analyzed that zero crossing rate is decreasing with increase the weight. When muscles are in rest position, there is no variation in EMG signal. While muscles are active for movement then amplitudes of the EMG signal increases so that zero crossing rate decreases.

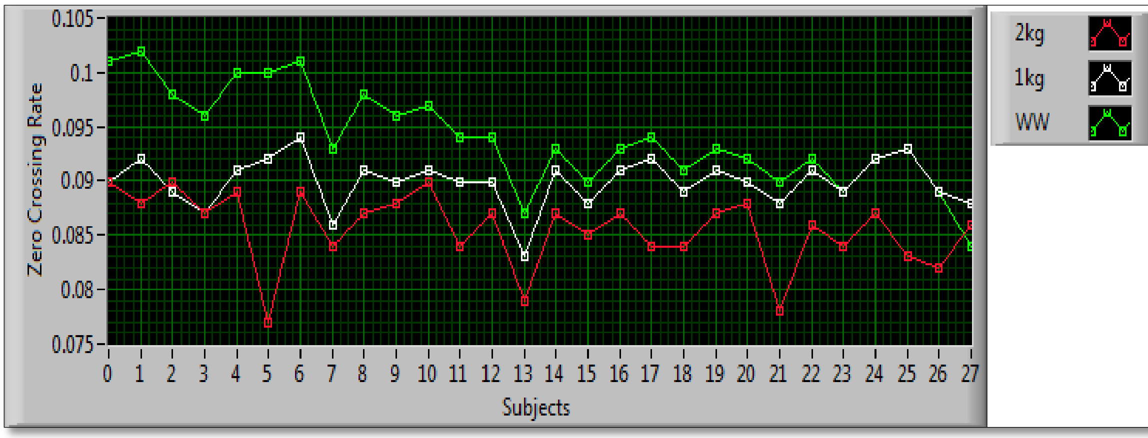

Fig. 5.3 (a) Zero crossing rate for grasp movement using different weights

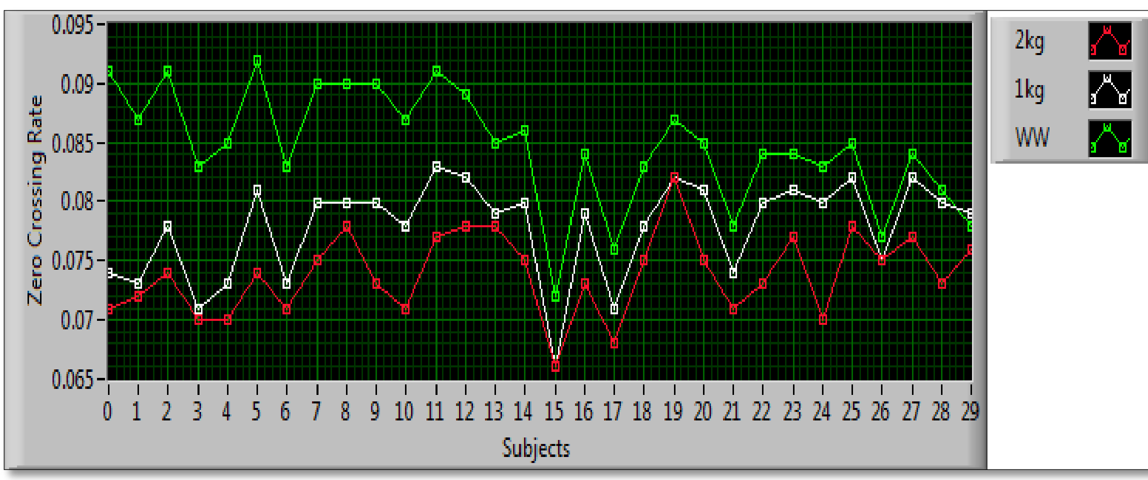

Fig. 5.3 (b) Zero crossing rate for lift movement using different weights

5.4 Classification of EMG Signals

Here, classifier is designed to a given set of data. Designed classifier gives quantitative output in the form of weights *i.e.* subject's grasp movement and lift movement. The classifier is tested with available set of data. The response of classifier to available 180 sample test data is evaluated and obtained results are shown in Table. 5.1-5.6

Table 5.1 Validation of classifier for grasp movement using without weight

Sample	**Zero crossing rate**	**Integrated EMG**	**Mean absolute value**	**Target**	**Output of classifier**
1	0.084	118427.114	7.228	WW	2 kg
2	0.093	89950.528	5.49	WW	WW
3	0.096	89842.341	5.484	WW	WW
4	0.09	112880.048	6.89	WW	1 Kg
5	0.089	112569.465	6.871	WW	2 Kg
6	0.087	154131.234	9.407	WW	2 Kg
7	0.101	88903.508	5.426	WW	WW
8	0.097	102156.21	6.235	WW	WW
9	0.101	97160.995	5.93	WW	WW
10	0.098	78119.46	4.768	WW	WW
11	0.093	100022.247	6.105	WW	WW
12	0.094	100237.379	6.118	WW	WW
13	0.093	92602.352	5.652	WW	WW
14	0.094	117254.859	7.157	WW	1 Kg
15	0.092	91461.34	5.582	WW	WW
16	0.098	106827.265	6.52	WW	WW
17	0.096	87653.375	5.35	WW	WW
18	0.093	86405.616	5.274	WW	WW
19	0.091	111600.219	6.812	WW	1 Kg
20	0.1	84584.24	5.163	WW	WW
21	0.093	100753.118	6.149	WW	WW
22	0.102	78008.567	4.761	WW	WW
23	0.1	78597.794	4.797	WW	WW
24	0.096	83789.012	5.114	WW	WW
25	0.092	85246.662	5.203	WW	WW
26	0.092	102655.948	6.266	WW	WW
27	0.089	103713.524	6.33	WW	1 Kg
28	0.094	94239.629	5.752	WW	WW
29	0.09	113015.997	6.898	WW	1 Kg
30	0.103	86227.88	5.263	WW	WW

Table 5.2 Validation of classifier for grasp movement using with 1 Kg weight					
Sample	**Zero crossing rate**	**Integrated EMG**	**Mean absolute value**	**Target**	**Output of classifier**
1	0.088	120615.713	7.362	1 Kg	1 Kg
2	0.091	94929.766	5.794	1 Kg	1 Kg
3	0.09	120454.197	7.352	1 Kg	1 Kg
4	0.088	134128.14	8.187	1 Kg	1 Kg
5	0.089	127653.514	7.791	1 Kg	2 Kg
6	0.083	172931.408	10.555	1 Kg	2 Kg
7	0.094	114245.369	6.973	1 Kg	1 Kg
8	0.091	115781.524	7.067	1 Kg	1 Kg
9	0.09	137218.193	8.375	1 Kg	2 Kg
10	0.089	118399.678	7.227	1 Kg	1 Kg
11	0.091	103935.581	6.344	1 Kg	WW
12	0.092	109080.7	6.658	1 Kg	WW
13	0.086	127091.659	7.757	1 Kg	2 Kg
14	0.09	135579.163	8.275	1 Kg	1 Kg
15	0.092	94123.167	5.745	1 Kg	WW
16	0.091	120507.841	7.355	1 Kg	1 Kg
17	0.087	106898.24	6.525	1 Kg	2 Kg
18	0.093	119979.501	7.323	1 Kg	1 Kg
19	0.089	134389.323	8.202	1 Kg	1 Kg
20	0.091	98072.254	5.986	1 Kg	WW
21	0.091	121505.144	7.416	1 Kg	1 Kg
22	0.092	91074.769	5.559	1 Kg	WW
23	0.092	108256.2	6.607	1 Kg	WW
24	0.092	84324.123	5.147	1 Kg	WW
25	0.09	102818.169	6.276	1 Kg	1 Kg
26	0.091	108886.541	6.646	1 Kg	1 Kg
27	0.089	104603.23	6.384	1 Kg	1 Kg
28	0.09	105632.403	6.447	1 Kg	1 Kg
29	0.088	123301.628	7.526	1 Kg	1 Kg
30	0.094	131079.77	8	1 Kg	1 Kg

Table 5.3 Validation of a classifier for grasp movement using with 2 Kg weight					
Sample	**Zero crossing rate**	**Integrated EMG**	**Mean absolute value**	**Target**	**Output of classifier**
1	0.086	141589.829	8.642	2 Kg	2 Kg
2	0.087	154149.697	9.409	2 Kg	2 Kg
3	0.088	148026.496	9.035	2 Kg	2 Kg
4	0.085	164963.577	10.069	2 Kg	2 Kg
5	0.084	180715.962	11.03	2 Kg	2 Kg
6	0.079	218397.794	13.33	2 Kg	2 Kg
7	0.089	140440.346	8.572	2 Kg	2 Kg
8	0.09	145288.543	8.868	2 Kg	2 Kg
9	0.09	152268.099	9.294	2 Kg	2 Kg
10	0.09	149524.117	9.126	2 Kg	2 Kg
11	0.087	125964.547	7.688	2 Kg	2 Kg
12	0.084	174975.031	10.68	2 Kg	2 Kg
13	0.084	156059.061	9.525	2 Kg	2 Kg
14	0.084	172163.388	10.508	2 Kg	2 Kg
15	0.087	138161.886	8.433	2 Kg	2 Kg
16	0.087	132308.864	8.075	2 Kg	1 Kg
17	0.087	118763.006	7.249	2 Kg	2 Kg
18	0.083	155959.879	9.519	2 Kg	2 Kg
19	0.084	163802.944	9.998	2 Kg	2 Kg
20	0.089	109575.281	6.688	2 Kg	1 Kg
21	0.087	137522.079	8.394	2 Kg	2 Kg
22	0.088	120633.473	7.363	2 Kg	1 Kg
23	0.077	146432.36	8.938	2 Kg	2 Kg
24	0.084	177721.545	10.847	2 Kg	2 Kg
25	0.088	115000.297	7.019	2 Kg	2 Kg
26	0.086	146311.332	8.93	2 Kg	2 Kg
27	0.082	159437.746	9.731	2 Kg	2 Kg
28	0.087	120360.946	7.346	2 Kg	2 Kg
29	0.078	235759.1	14.39	2 Kg	2 Kg
30	0.09	136281.668	8.318	2 Kg	2 Kg

Table 5.4 Validation of classifier for lift movement using without weight					
Sample	**Zero crossing rate**	**Integrated EMG**	**Mean absolute value**	**Target**	**Output of classifier**
1	0.077	162863.707	9.94	WW	2 Kg
2	0.086	132451.287	8.084	WW	WW
3	0.083	171239.337	10.452	WW	WW
4	0.084	141031.691	8.608	WW	WW
5	0.083	143412.056	8.753	WW	1 Kg
6	0.085	139516.515	8.515	WW	WW
7	0.09	120053.078	7.327	WW	WW
8	0.084	139331.095	8.504	WW	WW
9	0.085	130103.916	7.941	WW	WW
10	0.091	109902.476	6.708	WW	WW
11	0.087	133052.39	8.121	WW	WW
12	0.09	143183.143	8.739	WW	WW
13	0.083	144061.406	8.793	WW	WW
14	0.089	124886.673	7.622	WW	WW
15	0.091	101162.661	6.174	WW	WW
16	0.091	122361.068	7.468	WW	WW
17	0.087	108662.636	6.632	WW	WW
18	0.092	103590.988	6.323	WW	WW
19	0.076	213411.69	13.026	WW	2 Kg
20	0.084	129591.546	7.91	WW	1 kg
21	0.085	175921.532	10.737	WW	WW
22	0.078	255255.125	15.58	WW	2 kg
23	0.072	561810.104	34.29	WW	2 kg
24	0.078	172107.12	10.505	WW	2 Kg
25	0.085	143414.625	8.753	WW	WW
26	0.083	145937.69	8.907	WW	WW
27	0.081	194632.416	11.879	WW	1 Kg
28	0.084	140838.932	8.596	WW	WW
29	0.087	133725.908	8.162	WW	WW
30	0.09	123878.001	7.561	WW	WW

Table 5.5 Validation of classifier for lift movement using with 1 Kg weight					
Sample	**Zero crossing rate**	**Integrated EMG**	**Mean absolute value**	**Target**	**Output of classifier**
1	0.075	212875.596	12.993	1 Kg	2 Kg
2	0.08	180310.72	11.005	1 Kg	1 Kg
3	0.073	315901.897	19.281	1 Kg	2 Kg
4	0.081	160536.819	9.798	1 Kg	1 Kg
5	0.08	211018.989	12.88	1 Kg	1 Kg
6	0.079	210331.853	12.838	1 Kg	1 Kg
7	0.08	187093.187	11.419	1 Kg	1 Kg
8	0.079	162172.574	9.898	1 Kg	1 Kg
9	0.082	144715.513	8.833	1 Kg	1 Kg
10	0.074	233407.752	14.246	1 Kg	2 Kg
11	0.078	177428.659	10.829	1 Kg	1 Kg
12	0.08	241065.229	14.713	1 Kg	1 Kg
13	0.071	220507.949	13.459	1 Kg	2 Kg
14	0.082	166123.087	10.139	1 Kg	WW
15	0.078	202077.106	12.334	1 Kg	1 Kg
16	0.083	192656.361	11.759	1 Kg	1 Kg
17	0.082	135522.222	8.272	1 Kg	1 Kg
18	0.081	178647.935	10.904	1 Kg	1 Kg
19	0.071	335537.664	20.48	1 Kg	2 Kg
20	0.082	177560.296	10.837	1 Kg	1 Kg
21	0.081	189218.997	11.549	1 Kg	1 Kg
22	0.079	327839.97	20.01	1 Kg	1 Kg
23	0.066	963321.666	58.796	1 Kg	2 Kg
24	0.074	402701.373	24.579	1 Kg	2 Kg
25	0.073	235697.762	14.386	1 Kg	2 Kg
26	0.078	242103.552	14.777	1 Kg	2 Kg
27	0.08	252919.371	15.437	1 Kg	1 Kg
28	0.08	201528.867	12.3	1 Kg	1 Kg
29	0.073	253189.106	15.453	1 Kg	2 Kg
30	0.08	173143.104	10.568	1 Kg	1 Kg

Table 5.6 Validation of a classifier for lift movement using with 2 Kg weight					
Sample	**Zero crossing rate**	**Integrated EMG**	**Mean absolute value**	**Target**	**Output of classifier**
1	0.075	267503.398	16.327	2 kg	2 kg
2	0.075	238117.363	14.534	2 kg	2 kg
3	0.071	471072.61	28.752	2 kg	2 kg
4	0.077	205389.464	12.536	2 kg	2 kg
5	0.07	272778.661	16.649	2 kg	2 kg
6	0.078	290066.975	17.704	2 kg	2 kg
7	0.075	304824.905	18.605	2 kg	2 kg
8	0.073	288415.308	17.603	2 kg	2 kg
9	0.078	193882.741	11.834	2 kg	2 kg
10	0.071	308332.727	18.819	2 kg	2 kg
11	0.071	251167.99	15.33	2 kg	2 kg
12	0.078	296862.691	18.119	2 kg	2 kg
13	0.07	270573.238	16.514	2 kg	2 kg
14	0.078	191723.499	11.702	2 kg	2 kg
15	0.074	355662.368	21.708	2 kg	2 kg
16	0.077	269170.349	16.429	2 kg	2 kg
17	0.082	165753.344	10.117	2 kg	WW
18	0.074	301095.126	18.377	2 kg	2 kg
19	0.068	529930.352	32.344	2 kg	2 kg
20	0.077	240794.913	14.697	2 kg	2 kg
21	0.075	254422.304	15.529	2 kg	2 kg
22	0.076	411823.446	25.136	2 kg	2 kg
23	0.066	1171839.931	71.523	2 kg	2 kg
24	0.071	507929.823	31.002	2 kg	2 kg
25	0.07	333566.901	20.359	2 kg	2 kg
26	0.075	325734.893	19.881	2 kg	2 kg
27	0.073	431450.274	26.334	2 kg	2 kg
28	0.073	289585.629	17.675	2 kg	2 kg
29	0.072	267527.969	16.329	2 kg	2 kg
30	0.073	265526.862	16.206	2 kg	2 kg

Tables [5.1 – 5.6] show the feature extracted for a particular subject, corresponding expected output from classifier and the output provided by the classifier. The success rate of the classifier for individual movements is shown in Fig. [5.5(a) – 5.5(b)] and calculated using eq. 5.1.

$$Success\ Rate = \frac{No.of\ Successfull\ Trials}{Total\ number\ of\ Trials} * 100 \qquad 5.1$$

Success rate of classification

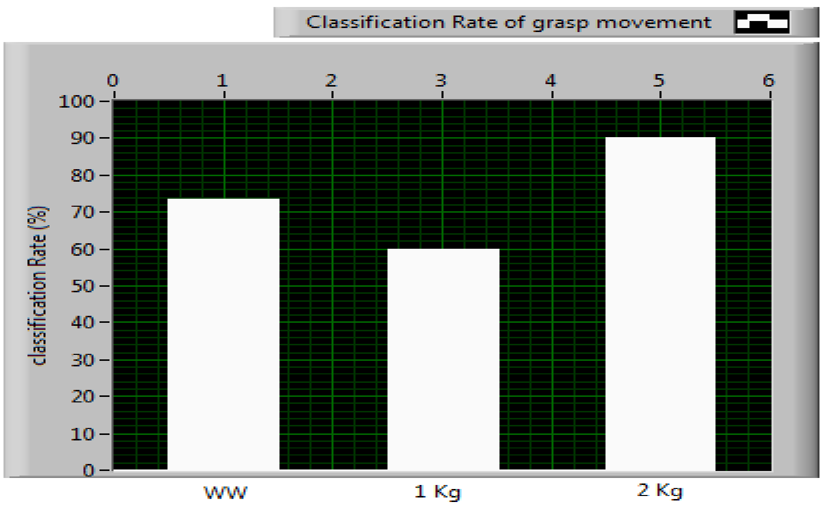

Fig. 5.5(a) Classification of grasp movement with different weights

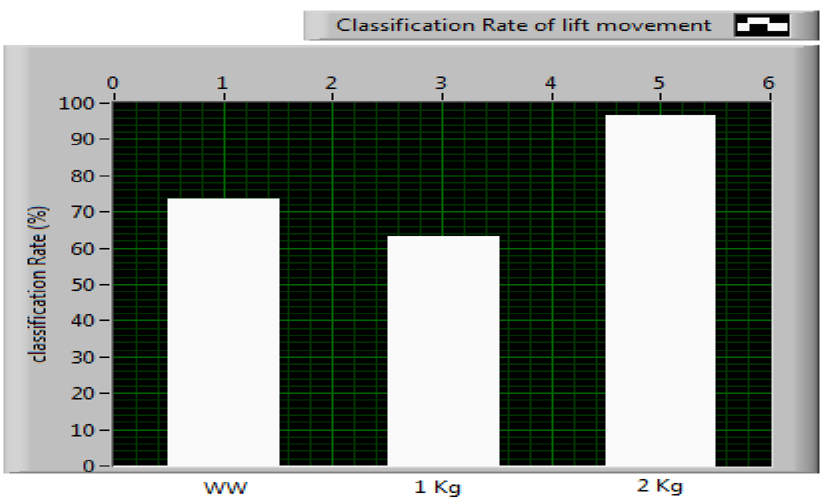

Fig. 5.5(b) Classification of lift movement with different weights

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

Conclusion

The SEMG signals are usually non-repeatable and contradictory in nature. Therefore, to classify such signal, a classifier able to withstand uncertainties in data is required. Fuzzy classifier has the capability to classify EMG signals. In the presented work feature extraction and classification of the EMG signal for two categories: grasping and lifting, and to provide quantitative information of weight held by the subject was done. The system was implemented in LabVIEW 2012 (evaluation version). To evaluate the performance of the implemented system was tested in 30 subjects with three weight combinations with no weight, 1 Kg weight and 2 Kg weight (180 sample). The results obtained show that the success rate of the classifier is 74.44 % (grasping) and 77.77 % (lifting).

It is also observed that the quality of EMG signals is affected by routine activity of the subject, which is reflected by the variations in root mean square value of the EMG signal.

The system is tested for both the male and female, the observations reveal that the performance remains unaffected.

Future Scope

In the presented work different rule base is designed for two actions grasping and lifting. A combined rule base can be designed to classify the actions and provide quantitative information of weight at the same time.

Further, the rule base can be reduced by using rule base reduction algorithms.

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APPENDIX A

Table A.1: Mean Absolute Value of Grasp movement

Subject	Without Weight	With 1Kg. Weight	With 2Kg. Weight
1	7.228	7.362	8.642
2	5.49	5.794	9.409
3	5.484	7.352	9.035
4	6.89	8.187	10.069
5	6.871	7.791	11.03
6	9.407	10.555	13.33
7	5.426	6.973	8.572
8	6.235	7.067	8.868
9	5.93	8.375	9.294
10	4.768	7.227	9.126
11	6.105	6.344	7.688
12	6.118	6.658	10.68
13	5.652	7.757	9.525
14	7.157	8.275	10.508
15	5.582	5.745	8.433
16	6.52	7.355	8.075
17	5.35	6.525	7.249
18	5.274	7.323	9.519
19	6.812	8.202	9.998
20	5.163	5.986	6.688
21	6.149	7.416	8.394
22	4.761	5.559	7.363
23	4.797	6.607	8.938
24	5.263	8	8.318
25	5.114	5.147	10.847
26	5.203	6.276	7.019
27	6.266	6.646	8.93
28	6.33	6.384	9.731
29	5.752	6.447	7.346
30	6.898	7.526	14.39

Table A.2 Root mean square value of Grasp movement

Subject	Without Weight	With 1Kg. Weight	With 2Kg. Weight
1	9.312	9.247	10.867
2	6.754	7.119	12.047
3	7.151	9.108	11.404
4	8.457	10.053	12.725
5	8.64	10.016	14.423
6	11.869	13.221	16.719
7	6.646	8.787	10.862
8	7.759	8.71	11.281
9	7.284	10.676	11.68
10	5.895	9.006	11.863
11	7.488	7.809	9.575
12	7.514	8.377	13.849
13	8.179	10.222	12.166
14	9.195	11.402	13.891
15	6.99	7.323	10.658
16	8.134	9.167	10.093
17	6.622	8.69	8.979
18	6.534	9.053	11.894
19	8.545	10.428	12.624
20	6.315	7.4	8.277
21	7.654	9.916	11.101
22	5.887	6.923	9.236
23	6.779	8.266	11.581
24	6.468	6.586	13.86
25	6.43	7.944	8.941
26	7.788	8.402	11.541
27	7.842	8.395	12.246
28	7.207	8.057	9.221
29	8.515	9.339	18.41
30	6.459	9.986	10.604

Table A.3: IEMG Value of Grasp movement

Subject	Without Weight	With 1Kg. Weight	With 2Kg. Weight
1	118427.1	120615.7	141589.8
2	89950.53	94929.77	154149.7
3	89842.34	120454.2	148026.5
4	112880	134128.1	164963.6
5	112569.5	127653.5	180716
6	154131.2	172931.4	218397.8
7	88903.51	114245.4	140440.3
8	102156.2	115781.5	145288.5
9	97161	137218.2	152268.1
10	78119.46	118399.7	149524.1
11	100022.2	103935.6	125964.5
12	100237.4	109080.7	174975
13	92602.35	127091.7	156059.1
14	117254.9	135579.2	172163.4
15	91461.34	94123.17	138161.9
16	106827.3	120507.8	132308.9
17	87653.38	106898.2	118763
18	86405.62	119979.5	155959.9
19	111600.2	134389.3	163802.9
20	84584.24	98072.25	109575.3
21	100753.1	121505.1	137522.1
22	78008.57	91074.77	120633.5
23	78597.79	108256.2	146432.4
24	86227.9	131080	136282
25	83789.01	84324.12	177721.5
26	85246.66	102818.2	115000.3
27	102655.9	108886.5	146311.3
28	103713.5	104603.2	159437.7
29	94239.63	105632.4	120360.9
30	113016	123301.6	235759.1

Table A.4: Zero Crossing Rate Values of Grasp movement

Subject	Without Weight	With 1Kg. Weight	With 2Kg. Weight
1	0.084	0.088	0.086
2	0.093	0.091	0.087
3	0.096	0.09	0.088
4	0.09	0.088	0.085
5	0.089	0.089	0.084
6	0.087	0.083	0.079
7	0.101	0.094	0.089
8	0.097	0.091	0.09
9	0.101	0.09	0.09
10	0.098	0.089	0.09
11	0.093	0.091	0.087
12	0.094	0.092	0.084
13	0.093	0.086	0.084
14	0.094	0.09	0.084
15	0.092	0.092	0.087
16	0.098	0.091	0.087
17	0.096	0.087	0.087
18	0.093	0.093	0.083
19	0.091	0.089	0.084
20	0.1	0.091	0.089
21	0.093	0.091	0.087
22	0.102	0.092	0.088
23	0.1	0.092	0.077
24	0.103	0.094	0.09
25	0.092	0.09	0.088
26	0.092	0.091	0.086
27	0.089	0.089	0.082
28	0.094	0.09	0.087
29	0.09	0.088	0.078
30	0.096	0.092	0.084

Table A.5: Root mean square value of lift movement

Subject	Without Weight	With 1Kg. Weight	With 2Kg. Weight
1	12.532	17.663	21.577
2	10.132	13.977	18.621
3	14.006	24.784	37.529
4	10.611	12.224	15.683
5	11.265	17.267	21.309
6	10.636	16.487	22.891
7	9.206	15.425	24.172
8	10.83	12.734	23.16
9	9.991	11.278	15.215
10	8.536	18.332	24.598
11	10.584	14.517	19.909
12	14.826	20.249	27.667
13	11.167	17.027	21.412
14	9.48	12.886	14.994
15	7.85	15.711	27.829
16	9.162	15.191	21.263
17	8.247	10.788	14.305
18	8.059	14.804	24.065
19	16.785	26.992	44.909
20	10.144	14.838	20.244
21	15.344	15.177	21.159
22	21.002	26.184	32.332
23	53.137	83.124	109.199
24	13.603	32.205	41.28
25	12.503	20.159	29.126
26	11.224	19.941	27.907
27	15.159	22.898	34.521
28	10.88	16.129	23.756
29	10.202	19.833	21.026
30	9.635	13.917	21.647

Table A.6: Zero crossing rate for lift movement

Subject	Without Weight	With 1Kg. Weight	With 2Kg. Weight
1	0.077	0.075	0.075
2	0.086	0.08	0.075
3	0.083	0.073	0.071
4	0.084	0.081	0.077
5	0.083	0.08	0.07
6	0.085	0.079	0.078
7	0.09	0.08	0.075
8	0.084	0.079	0.073
9	0.085	0.082	0.078
10	0.091	0.074	0.071
11	0.087	0.078	0.071
12	0.09	0.08	0.078
13	0.083	0.071	0.07
14	0.089	0.082	0.078
15	0.091	0.078	0.074
16	0.091	0.083	0.077
17	0.087	0.082	0.082
18	0.092	0.081	0.074
19	0.076	0.071	0.068
20	0.084	0.082	0.077
21	0.085	0.081	0.075
22	0.078	0.079	0.076
23	0.072	0.066	0.066
24	0.078	0.074	0.071
25	0.085	0.073	0.07
26	0.083	0.078	0.075
27	0.081	0.08	0.073
28	0.084	0.08	0.073
29	0.087	0.073	0.072
30	0.09	0.08	0.073

Table A.7: Mean absolute value for lift movement

Subject	Without Weight	With 1Kg. Weight	With 2Kg. Weight
1	9.94	12.993	16.327
2	8.084	11.005	14.534
3	10.452	19.281	28.752
4	8.608	9.798	12.536
5	8.753	12.88	16.649
6	8.515	12.838	17.704
7	7.327	11.419	18.605
8	8.504	9.898	17.603
9	7.941	8.833	11.834
10	6.708	14.246	18.819
11	8.121	10.829	15.33
12	8.739	14.713	18.119
13	8.793	13.459	16.514
14	7.622	10.139	11.702
15	6.174	12.334	21.708
16	7.468	11.759	16.429
17	6.632	8.272	10.117
18	6.323	10.904	18.377
19	13.026	20.48	32.344
20	7.91	10.837	14.697
21	10.737	11.549	15.529
22	15.58	20.01	25.136
23	34.29	58.796	71.523
24	10.505	24.579	31.002
25	8.753	14.386	20.359
26	8.907	14.777	19.881
27	11.879	15.437	26.334
28	8.596	12.3	17.675
29	8.162	15.453	16.329
30	7.561	10.568	16.206

Table A.8: IEMG value for lift movement

Subject	Without Weight	With 1Kg. Weight	With 2Kg. Weight
1	162863.707	212875.596	267503.398
2	132451.287	180310.72	238117.363
3	171239.337	315901.897	471072.61
4	141031.691	160536.819	205389.464
5	143412.056	211018.989	272778.661
6	139516.515	210331.853	290066.975
7	120053.078	187093.187	304824.905
8	139331.095	162172.574	288415.308
9	130103.916	144715.513	193882.741
10	109902.476	233407.752	308332.727
11	133052.39	177428.659	251167.99
12	143183.143	241065.229	296862.691
13	144061.406	220507.949	270573.238
14	124886.673	166123.087	191723.499
15	101162.661	202077.106	355662.368
16	122361.068	192656.361	269170.349
17	108662.636	135522.222	165753.344
18	103590.988	178647.935	301095.126
19	213411.69	335537.664	529930.352
20	129591.546	177560.296	240794.913
21	175921.532	189218.997	254422.304
22	255255.125	327839.97	411823.446
23	561810.104	963321.666	1171839.931
24	172107.12	402701.373	507929.823
25	143414.625	235697.762	333566.901
26	145937.69	242103.552	325734.893
27	194632.416	252919.371	431450.274
28	140838.932	201528.867	289585.629
29	133725.908	253189.106	267527.969
30	123878.001	173143.104	265526.862