NEUROMUSCULAR ACTIVITY CLASSIFICATION BASED ON AUTOREGRESSIVE MODELING OF TIME-FREQUENCY DOMAIN DECOMPOSED SURFACE EMG SIGNAL

By

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The thesis entitled " **NEUROMUSCULAR ACTIVITY CLASSIFICATION BASED ON AUTOREGRESSIVE MODELING OF TIME-FREQUENCY DOMAIN DECOMPOSED SURFACE EMG SIGNAL"** submitted by Md. Gholam Rosul, Student No: 1014062261, Session: October, 2014 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of MASTER OF SCIENCE IN ELECTRICAL AND ELECTRONIC ENGINEERING on Apr 16,2018.

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I, do, hereby declare that neither this thesis nor any part of it has been submitted elsewhere for the award of any degree or diploma.

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Grosul

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DEDICATION

To

Dr. Shaikh Anowarul Fattah

Dr. Celia Shahnaz

Afsana Yesmin (Wife)

AayanAhnaf (Son)

and

My Parents

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ABSTRACT

Electromyography (EMG) measures electrical activity in the muscle due to neuromuscular activities. It is acquired either by needle (nEMG) or by surface (sEMG) electrodes. The sEMG is getting popularly because of its non-invasive acquisition technique and widely used in prosthetic control and human-machine interaction. However, due to noise like characteristics of sEMG signals, poor performance may be obtained for classifying similar types of neuromuscular actions, especially when only a single lead data are used. In this thesis, efficient schemes are proposed to classify neuromuscular activities based on autoregressive (AR) reflection coefficients extracted from single lead original and decomposed sEMG signals. At first a given frame of raw sEMG signal is divided into short duration sub-frames and considering AR modeling, from each sub-frame AR reflection coefficients are extracted. Instead of using the entire frame at a time, sub-frame based AR analysis is expected to provide consistent estimates and capture short duration variations. The advantages of using AR reflectioncoefficients over the conventional AR parameters are that their values are bounded (0 to 1) and they provide better consistency, noise immunity and lower computational complexity. The reflection coefficients obtained from each sub-frame are finally averaged to construct the proposed feature vector. In the second scheme, in view of investigating the effect of utilizing the decomposed sEMG data, singular value decomposition (SVD) is performed on each sub-frame of sEMG data. Next, instead of using the original sEMG data, decomposed data is used for extracting the AR reflection coefficients. In order to analyze the effect of time-frequency domain decomposition of the sEMG data on the extracted feature quality, in the third scheme, the discrete wavelet transform (DWT) is chosen. Each sub-frame of sEMG data is decomposed by using the DWT and then both the approximate and detailed coefficients are then used for extracting AR reflection coefficients. For the purpose of classification, the k-nearest neighborhood (KNN)classifier is applied in a hierarchical approach. The proposed method is tested on a publicly available sEMG dataset containing six different hand movements collected from three females and two males. It is observed that the proposed method offers consistently a very high accuracy in classifying the hand movements using a very low feature dimension.

Contents

Dedication iii

Acknowledgements iv

Abstract v

Chapter 1 Introduction 1

1.1 Background of Neuromuscular Activity……………………….................1

1.2 Electromyography (EMG) Signal Collection Process…………………….3

1.3 Neuromuscular Activity Classification of EMG Signal.……....................6

1.4 Literature Review...……………………………………………………..8

1.5 Thesis Motivation………………………………………………………..10

1.6 Thesis Objective…………………………………………………………11

1.7 Organization of the Thesis…..……………………………………….....11

Chapter 2 Hand Movement Classification Using Autoregressive ReflectionCoefficient

2.1 Introduction…………………………………………….....................12

2.2 Database……………………………..…………………........................13

2.3 Proposed Method………………………………………………………...18

2.3.1 SubFraming……………………….……………………………18

2.3.2 Feature Extraction………………………………..........................19

2.3.3 Classification…………………………………………………..21

2.4 Simulation Results…..……………………………….........................22

2.5 Conclusion……..…………………………………….........................28

Chapter 3 Hand Movement Recognition Using Singular Value Decomposition of Surface EMG Signal

3.1 Introduction……………………………………………………...................29

3.2 Proposed Method…………………………………………………………...30

3.2.1 Sub-Framing……………………………….............................31

3.2.2 Feature Extraction..……………………………….....................31

3.2.3 Classification…………………………………………………..33

3.3 Simulation Results………………………………………………………….33

3.4 Conclusion……..…………………………………………………………...39

Chapter 4 Hand Movement Recognition Using Discrete Wavelet Transform of Surface EMG Signal

4.1 Introduction………………………………………….........................40

4.2 Proposed Method…………………………………………………...41

4.2.1 Sub-Framing……………………………….............................42

4.2.2 DWT Based Feature Extraction …………………………………43

4.2.3 Classification…………………………………………………..46

4.3 Simulation Results…...……………………………………………….47

4.4 Conclusion……..…………………………………………………...47

Chapter 5 Conclusion

5.1 Contribution of the Thesis……………………………………………49

5.2 Scope and Future Work………………………………........................51

Bibliography…………………………………………………………………………52

List of Tables

2.1 Comparison of Classification Accuracy Obtained Using Autoregressive Reflection Coefficient……………………….........................23

2.2 Confusion Matrix for Female 2………………………………….....................24

2.3 Confusion Matrix for Male 2……………………………………………………24

3.1 Comparison of Classification Accuracy UsingSingular Value Decomposition...34

3.2 Confusion Matrix for Male 2……………………………………………………35

3.3 Confusion Matrix for Female 1………………………………….....................35

4.1 Comparison of Classification Accuracy UsingDiscrete Wavelet Transform…...47

List of Figures

1.1 Surface EMG electrodes and its placement……………………………………….4
1.2 Different indwelling needle electrode types……………………………………5
1.3 Electromyography (EMG) Signal………………………………...…………6
1.4 Surface EMG recording and sample plot……………………..…......................7
1.5 Surface Electromyogram (sEMG) versusNeedle Electromyogram(nEMG).......8
2.1 Illustration of the hand movement……………………………………………….14
2.2 Energy Curve for Spherical Movement………………………………………….15
2.3 Energy Curve for Tip Movement………………………………………………...15
2.4 Energy Curve for Palmar Movement…………………………………………….16
2.5 Energy Curve for Lateral Movement…………………………………………….16
2.6 Energy Curve for Cylindrical Movement………………………………………..17
2.7 Energy Curve for Hook Movement……………………………………………...17
2.8 Block diagram explaining the Autoregressive Reflection Coefficient method…18
2.9 How reflection coefficients vary with trial in the case of each action of female 1 when filterorder is 20 and filter order is 10…………….....................................25
2.10 How reflection coefficients vary with trial in the case of each action of female 2 when filter order is 20 and filter order is 10…………….....................................25
2.11 How reflection coefficients vary with trial in the case of each action of male 2 when filter order is 20 and filter order is 10……………………………………..26
2.12 How accuracy varies for different AR model order for male 2…………………27
2.13 How accuracy varies for different AR model order for all five subjects……………………………………….…………….……………...27
3.1 Block diagram explaining the proposed SVD based method……………………30
3.2 Sub-frame signal versus SVD signal…………………………………………….33
3.3 How energies vary with singular values of trials in the case of each action of male 1……………………………………………………………………………..36
3.4 How energies vary with singular values of trials in the case of each action of female 2 when sub-frame is 20……………………………….…………………37
3.5 How accuracy happens to vary for different sub-frame durations in the case of female 2……………………………………………….................................38
3.6 How accuracy happens to vary for different sub-frame durations in the case of male 1…………………………………………………………………………….38
4.1 Block diagram explaining the proposed DWT based method…………………...42
4.2 300 msec long overlapping windows to compute the DWT……….....................43
4.3 Block diagram representing the level-1 DWT on sEMG signal…………………44
4.4 Sub-frame Signal versus DWT (cA and cD) Signal……………………………..45

Chapter 1

Introduction

1.1 Background of Neuromuscular Activity

Biomedical signal means a collective electrical signal acquired from any organ that represents a physical variable of interest. This signal is normally a function of time and is describable in terms of its amplitude, frequency and phase. The electromyography (EMG) signal is a biomedical signal that measures the electrical potentials generated in muscles during neuromuscular activities. For example, to conduct any limb movement, first the brain needs to generate and transmit neural signal (via neuro-transmitter) and then muscle generates motor unit action potentials (MUAPs) in response to those neural signals, which can be observed in the recorded EMG signals. Human nervous system always controls the muscle activity (contraction/relaxation) in response to several parallel tasks to be carried out by various organs and thus the EMG signal corresponding to the neuromuscular activities is a very complicated signal. The variation in the amplitudes of EMG signal is controlled by the nervous system and depends on the anatomical and physiological properties of muscles. The EMG serves as a reliable source of information about different features of muscle function.

Recording of EMG signals can be achieved by placing electrodes on the surface of the skin (surface EMG) or fine wire or needle electrodes which are inserted deep in the muscle (indwelling/needle EMG). When recording from deep within the muscle, a needle or fine wire electrode is inserted into the muscle (approximately 0:25-0.5cm deep). An advantage of needle EMG is its selectivity which strongly attenuates cross talk (a phenomenon in which action potentials from muscles further away also contribute to the recording through volume conduction contributing to the recorded EMG signal), and can be used when targeting small muscles. However in most of the applications it is not feasible to use needle EMG because of its invasive nature. As a result use of surface EMG (sEMG) is getting popularity and in neuromuscular activity detection sEMG is mainly used now-a-days.

The study of EMG is originated from the discovery of the role that electricity plays in the nervous system of animals. The first written documents on bioelectric events, which describes the catfish as a fish that "releases troops" due to the electric shocks it generated, can be found in the ancient Egyptian hieroglyph of 4000 B.C. Francesco Redi, in the mid 1600's, documented that a highly specialized muscle was the source of an electric ray fish's energy. Direct observation of the relationship between muscles and electricity was performed in dissected frogs, by Luigi Galvani (1791- 1797). Galvani's results enticed Alessandro Volta to develop the Voltaic pile, the earliest known electric battery. He then used it to study animal electricity (such as electric eels) and the physiological responses to applied direct-current voltages. Also, following Galvani's work, Carlo Matteucci demonstrated that cell membranes had a voltage across them and could produce direct current. German physiologist Emil du Bois-Reymond, who was inspired by Matteucci's work, went on to discover the action potential in 1848. The conduction velocity of action potentials was first measured in 1850 by du Bois-Reymond's friend, Hermann von Helmholtz. In 1880, Wollaston hypothesized that a sound is generated during muscle contraction. Due to limitations technologically, he proved his theory by comparing the frequency of muscle sounds to distant carriages moving along cobblestone roads. A carriage was driven at various speeds until the noise frequency generated from the carriage matched that of contracting muscle that Wollaston heard through his thumbs. By knowing the size of cobblestones and the diameter of the carriage wheels, Wollaston estimated the sound generated by muscles to be approximately 25 Hz. In this way, he demonstrated that energy generated by muscles was in a range that is audible. To establish that nervous tissue was made up of discrete cells, the Spanish physician Santiago Ramny Cajal and his students used a stain developed by Camillo Golgi to reveal the myriad shapes of neurons. For their discoveries, Golgi and Ramny Cajal were awarded the 1906 Nobel Prize in Physiology. EMG signals were first displayed on an oscilloscope in the 1920's. This advance intellectually stimulated researchers to further investigate the anatomy and physiology of skeletal muscles. As a result, investigators such as Basmajian have been able to demonstrate a deeper comprehension of EMG and its application. This knowledge has increased the curiosity among several investigators in the field of electromyography.

1.2 EMG Signal Collection Process

Methods used to acquire data are heavily dependent on the nature of signals to be acquired. EMG signals are complex signals, controlled by the nervous system and are dependent on the anatomical and physiological properties of muscles. Also, it is important to realize that just like any other signals in transit, the EMG signal gets contaminated with undesirable signals (noise) as it traverses from its source to the recording apparatus, making it very difficult to detect. Fortunately, there are techniques that can be used to minimize noise embedded in signals. One such technique is through the process of differential amplification. As a result, the recording of small signals buried in larger common signals is possible. Employing similar techniques, small EMG signals can reliably (high signal to noise ratio) be detected and recorded. Care should be taken when selecting electrodes and type of amplifiers. Electrode and internal amplifier noise may distort the recording of the EMG signal. Filtering is normally performed so that unwanted signals such as low frequency motion artifacts are removed from the EMG signal. With regards to recording the EMG signal, the amplitude of the motor unit action potential depends on many factors which include: diameter of the muscle fiber, distance between active muscle fibers and the detection site (adipose tissue thickness), and filtering properties of the electrodes themselves. The objective is to obtain a signal free of noise (i.e. movement artifact, 50 Hz artifact, etc.). Therefore, the electrode type and amplifier characteristics play a crucial role in obtaining a noise-free signal.

For EMG signal acquisition, there are two main types of electrodes: surface and fine wire/ indwelling. The surface electrodes are also divided into two groups. The first is active electrodes, which have built-in amplifiers at the electrode site to improve the impedance (no gel is required for these and they decrease movement artifacts and increase the signal to noise ratio). The other is a passive electrode, which detects the EMG signal without a built-in amplifier, making it important to reduce all possible skin resistance as much as possible (requires conducting gels and extensive skin preparation). With passive electrodes, signal to noise ratio decreases and many movement artifacts are amplified along with the actual signal once amplification occurs.

Some major advantages of surface electrodes are that there is minimal pain with application, they are more reproducible, they are easy to apply, and they are very good for movement applications. The disadvantages of surface electrodes are that they have a large pick-up area and therefore, have more potential for cross talk from adjacent muscles. Additionally, these electrodes can only be used for surface muscles. Fig. 1.1 illustrates some of these EMG electrodes and its placement in hand. Fine wire electrodes require a needle for insertion into the belly of the muscle. The advantages of fine wire electrodes are an increased band width, a more specific pick-up area, ability to test deep muscles, isolation of specific muscle parts of large muscles and ability to test small muscles which would be impossible to detect with a surface electrode due to cross-talk.

Figure 1.1: Surface EMG electrodes and its placement

The disadvantages are that the needle insertion causes discomfort, the uncomfortableness can increase the tightness or spasticity in the muscles, cramping sometimes occurs, the electrodes are less repeatable as it is very difficult to place the needle/fine wires in the same area of the muscle each time. However, for certain muscles, fine wires are the only possibility for obtaining their information. The most common indwelling electrodes used to record EMG are monopolar and concentric needle electrodes. In addition there are other EMG recording techniques based on special needle electrode configurations, namely: single-fiber EMG, macro EMG and quadrifilar needle electrode. Fig. 1.2 illustrates some of these EMG needle types.

Electrical activity of the muscle is usually of very low voltage (generally less than 5-10mV). It is therefore essential to amplify the detected EMG signal so that the signal can be sampled reliably by typical analog to digital converters. Boosting a signal's gain is achieved by using an amplifier. The differential input, single-ended output instrumentation amplifier is one of the most useful signal processing amplifiers. It is used for precision amplification of differential dc or ac signals while rejecting large values of common mode interference. It is essential that the EMG signal is amplified without distortion. Ideally, the EMG amplifying circuit should possess the following characteristics:

1. High common mode rejection ratio.
2. High slew rate/bandwidth.
3. Very high input impedance.
4. Short distance to the signal source.

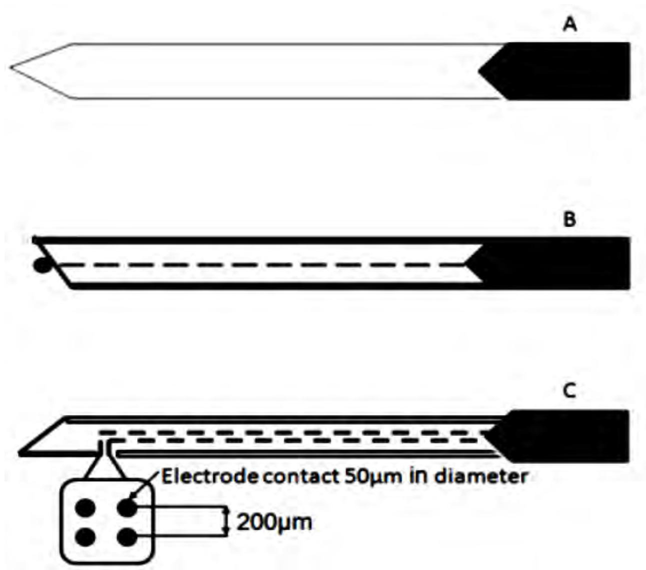

Figure 1.2: Different indwelling needle electrode types. A) In the monopolar design, the needle is Teflon coated and its exposed tip serves as the active electrode. B) The concentric needle has an active electrode running as a thin wire through the needle center and exposed at the tip. The canola serves as reference. C) The quadrifilar needle electrode is 25 gauge stainless steel. The needle electrode was custom designed with four 50 μm platinum wire electrodes equably exposed on the side port of the canola.

1.3 Neuromuscular Activity Classification of Surface EMG Signal

For conducting any limb movement or activities, first brain needs to generate and transmit neural signal (via neuro-transmitter). Muscle generates motor unit action potentials in response to neural signal, which can be extracted from EMG data. The EMG is a technique utilized to evaluate and record electrical activity generated by skeletal muscle. Electromyography (EMG) refers to the collective electric signal from muscles, which is controlled by the nervous system and produced during muscle contraction. The signal represents the anatomical and physiological properties of muscles; in fact, an EMG signal is the electrical activity of a muscle's motor units. Motor unit action potential (MUAP) can be studied by recording muscles electrical activity. In clinical EMG MUAPs are recorded using a needle electrode at slight voluntary contraction. The MUAP reflects the electrical activity of a single anatomical motor unit. It represents the compound action potential of those muscle fibers within the recording range of the electrode. EMG testing has a variety of clinical, biomedical and human-machine interaction (HMI) applications. It can be used for identifying neuromuscular diseases or to detect level of muscle fatigue and disorders of motor control or identifying various limb movements. EMG signals are also used as a control signal for prosthetic devices such as prosthetic hands, arms, and lower limbs. In Figure 1.3, a sample EMG signal is shown.

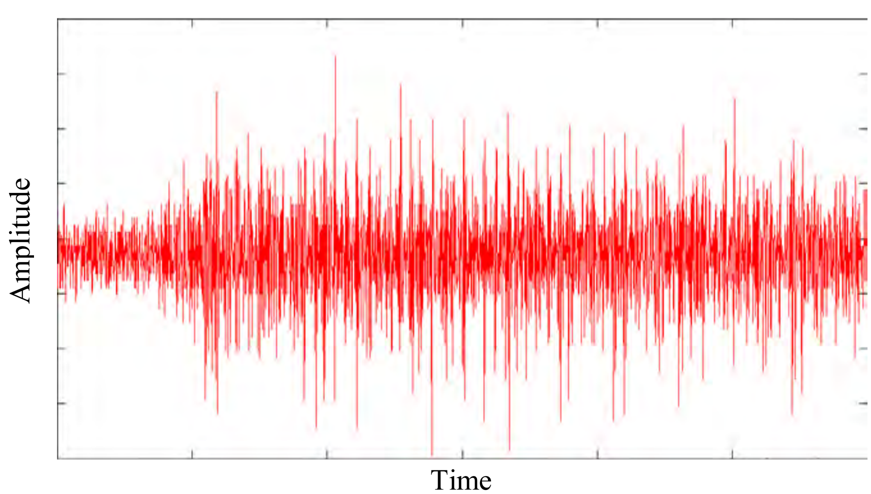

Figure 1.3: Electromyography (EMG) Signal

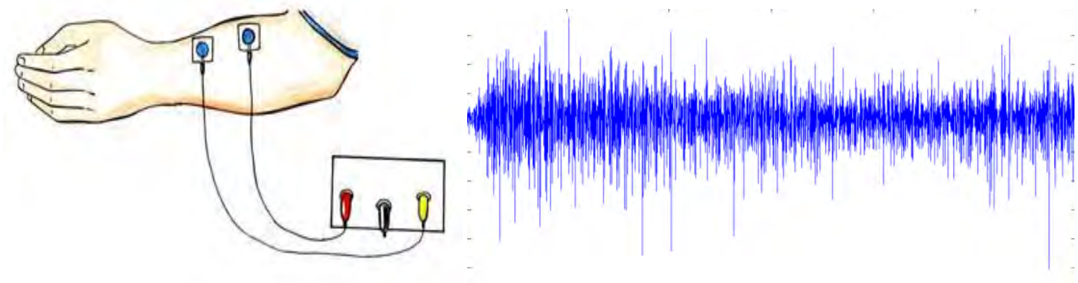

Figure 1.4: Surface EMG recording and sample plot

There are two kinds of EMG: surface EMG (sEMG) and intramuscular EMG (iEMG) or needle EMG (nEMG). Surface EMG assesses muscle function by recording muscle activity from the surface above the muscle on the skin as depicted in Figure 1.4. Needle EMG is recorded using needle electrode inserted into a muscle for exact detection of the signal from contracted muscle. Intramuscular EMG is an invasive process, thus is not applicable for purposes other than disease detection. On the other hand surface EMG is non-invasive and can be simply recorded from above the surface of the skin. As a result widespread potential applications for surface EMG signal classification and control have been reported in the last two decades; including multifunction prosthesis, electrical wheelchairs, virtual mouse and keyboard and virtual worlds.

In Figure 1.5, samples of sEMG and nEMG are shown. Surface EMG can be recorded by a pair of electrodes or by a more complex array of multiple electrodes (Figure 1.4). More than one electrode is needed because EMG recordings display the potential difference (voltage difference) between two separate electrodes. But working with surface EMG brings about some challenges due to the fact that surface electrode recordings are restricted to superficial muscles, influenced by the depth of the subcutaneous tissue at the site of the recording which can be highly variable depending of the weight of a patient and cannot reliably discriminate between the discharges of adjacent muscles.

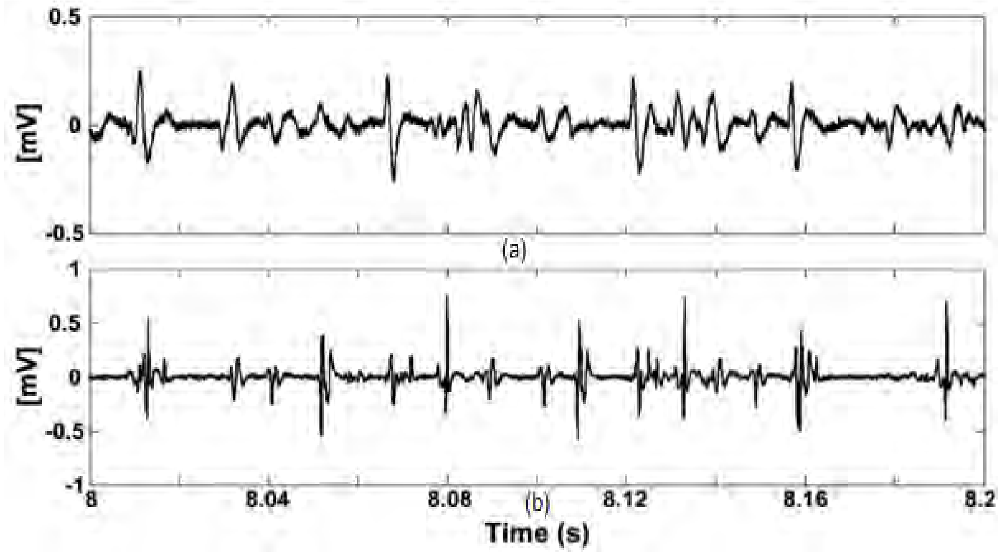

Figure 1.5: Samples of (a) surface EMG (sEMG) and (b) needle EMG (nEMG)

1.4 Literature Review

More than 100 neuromuscular disorders that attack the spinal cord, nerves or muscles are present. Early finding and diagnosis of these diseases by clinical examination and laboratory tests is crucial for their management as well as their anticipation through prenatal diagnosis and genetic counseling. Such information is also valuable in research, which may lead to the understanding of the nature and eventual treatment of these diseases. One of the earliest methods for quantitative EMG decomposition was developed by Buchthal et al. [32], where MUAPs were recorded photographically and then analyzed heuristically. Manual methods, although important at the time, were time consuming and liable to variable errors due to the subjective measurement of the MUAP parameters of interest. LeFever and DeLuca [33] used a special three channel recording electrode and a visual-computer decomposition scheme based on template matching and firing statistics for MUAP identification. Stalberg et al. [34] in their original system used waveform template matching, whereas more recently they used different shape parameters as input to a template matching technique. Bischoff et al. [35] reported a method to identify MUAPs based on power spectrum matching. Fang et al. [36] developed a comprehensive technique to identify single MUAP based on one-channel EMG recordings measuring waveform similarity of single MUAP in the wavelet domain. Wu et al. [37] decomposed MUAPs of needle electrode EMG signal by means of self-organization competing neural network. Chauvet et al. [38] proposed a method that allows decomposition of EMG signals based on fuzzy logic techniques. Zennaro et al. [39] designed decomposition software for multichannel long-term EMG recordings using a wavelet-based hierarchical cluster analysis algorithm, which is suitable for the study of MU discharge patterns in healthy subjects. MUAP classification into normal, myopathic and neuropathic categories has been introduced by Coatrieux [40].

Features of MUAPs extracted in the time domain such as duration, amplitude and phases proved to be very helpful in differentiating between muscle and nerve diseases with the duration measure being the key parameter used in clinical practice. With increasing muscle force, the EMG signal shows an increase in the number of activated MUAPs recruited at increasing firing rates, making it difficult for the neurophysiologist to distinguish the individual MUAP waveforms. EMG signal decomposition and MUAP classification into groups of similar shapes give significant information for the assessment of neuromuscular pathology. Nevertheless, the measurement of the duration parameter is a complicated task depending on the neurophysiologist and/or the computer-aided method used. The description of an extensively accepted criterion that will allocate the computer aided measurement of this parameter is still absent. On the other hand, frequency domain features of MUAPs like the mean or median frequency, bandwidth and quality factor give supplementary information for the assessment of neuromuscular disorders and it has recently been shown that the discriminative power of the MUAP mean or median frequency is comparable to the duration measure or the spike duration measure. Recent advances in computer technology have made automated EMG analysis feasible. Although a number of computer-based quantitative EMG analysis algorithms have been developed, some of them are commercially available, practically none of them have gained broad acceptance for widespread routine clinical use. Pattichis and Elia [41] used autoregressive and cepstral analyses combined with time domain analysis in classification of EMG signals. Also De Michele et al. [42] described how the proper use of the wavelet cross-correlation analysis on surface signals of the above two different muscles allows a more comprehensive classification of subjects and at the same time, a reliable temporal evolution analysis of Parkinson's disease. Pattichis et al. [43] used MUAP parameters as input to a sequential parametric pattern recognition classifier. Loudon et al. [44] used eight features as input to a statistical pattern recognition technique for classification. The decomposition of superimposed waveforms used a combination of procedural and knowledge-based methods. Finally Hassoun et al. [45] proposed a system called neural network extraction of repetitive vectors for electromyography (NNERVE) and they used the time domain waveform as input to a three-layer artificial neural network (ANN) with a "pseudo unsupervised" learning algorithm for classification. However, although some of these methods produce adequate results, none can offer interpretation of the classification results. In addition, Schizas and Pattichis [46] used genetics based machine learning as pattern classifiers in EMG. There are numerous limitations in the existing quantitative EMG analysis methods, which limit their wider applicability in various applications. Classification of raw EMG signal has also been done with notable accuracy. Using fast Fourier transformation the EMG power spectrum was examined to classify EMG signals. Autoregressive (AR) and the WT domain feature based classification of EMG signals were proposed using neuro-fuzzy classifiers [47]-[48].

1.5 Thesis Motivation

In order to construct an autonomous system for a hand amputee, the control of the robotic exoskeleton is a challenge. The utilization of EMG signals seems to be a viable solution since every movement has a distinct signature on the produced signal. Several approaches to solve the motion command identification problem using EMG signals have been suggested, achieving in some cases low classification error, using not necessarily typical daily hand’s movements and a large number of electrodes (in most of the cases more than 4). This is an issue that can have a negative impact in the expenditure for the construction of a system that consists of sensors and electrodes and it may not be so comfortable and acceptable from a hand amputee. Therefore, it would be desirable, for a dexterous prosthesis, to let the amputee command a grasp posture and force, just by performing the corresponding action with the exoskeleton prosthetic hand. Also, a way to finely modulate the force involved in a grasp is paramount in daily life activities, for example to hold a credit card, a glass of water, a pencil, a ball without breaking it or to grasp a hammer without letting it slip. Moreover, it is more comfortable for a hand amputee to wear a glove that includes the EMG electrodes than using the rather promising electroencephalography (EEG) electrodes in the area of the head. This issue is of significant importance for using such a system in a daily basis [1].

1.6 Thesis Objective

The objectives of this thesis are:

I. To analyze sub-frame based characteristic variation of sEMG signal for various neuromuscular tasks.

II. To investigate variations of decomposed sEMG signals by utilizing various types of time and frequency domain decompositions techniques.

III. To extract autoregressive reflection coefficient features from decomposed as well as original sEMG data.

IV. To develop efficient classification scheme to classify various types of neuro-muscular movements.

1.7 Organization of the Thesis

The rest of the thesis is organized as follows:

In Chapter 2, a method for hand movement classification using autoregressive reflection coefficient features extracted from surface EMG Signal is discussed.

In Chapter 3, a method for hand movement recognition using singular value decomposition followed by reflection coefficient extraction from surface EMG signal is discussed.

In Chapter 4, a method for hand movement recognition using discrete wavelet transform (DWT) of surface EMG signal followed by AR analysis in transform domain is proposed.

In Chapter 5, the contribution of the thesis is summarized.

Chapter 2

Hand Movement Classification Using Autoregressive Reflection Coefficient

2.1 Introduction

Electromyography (EMG) measures electrical activity in the muscle in response to nerve's stimulation. The surface EMG is gaining popularity because of its non-invasive acquisition technique and now it is being widely used in the field of biomedical engineering for different applications, such as prosthetic control, diagnosis of neuromuscular diseases, muscle injury detection, and rehabilitation. Prosthetic arms play a very valuable role as replacement to amputees [16]. In comparison to EEG, the myoelectric prosthetic arm is more convenient, which uses the EMG signals from the patient's available organ and controls movement of the prosthetic arm [17]. Accuracy in classifying received sEMG signal dictates the efficient control strategies of a robotic hand with the advances in biosensors, pattern recognition and bio-signal processing [18]-[20]. The use of sEMG signals for upper limb prosthesis control has attracted several researchers for a long time.

For the identification of motion command from sEMG signals, different approaches have been suggested so far, where a large number of electrodes and a typical daily hand movement have been utilized. Hand action classification has been investigated by several research groups previously by using complex methods of decomposition and extraction of a large number of features from the decomposed signals. By performing empirical mode decomposition (EMD) on the raw sEMG signals followed by feature extraction, six different hand actions have been classified [9]. In this case, eight statistical features are extracted, namely integrated EMG, zero-crossing, variance, slope-sign change, waveform length, Willison amplitude, kurtosis and skewness. In [11], both time and frequency domain features are extracted to classify hand actions from sEMG data. In [15], six wrist motions are classified based on two-channel sEMG signals using linear kernel support vector machine classifier. In [8], four hand motions are classified by the extraction of three time domain features from sEMG signals. In most of the cases, it is observed that the classification depends strongly on the action types and due to complicated characteristics of sEMG signals compared to needle EMG signals, poor performance may occur for similar types of actions or actions that involve less number of motor neurons. A simple but efficient sEMG feature extraction scheme that offers very satisfactory classification performance with low feature dimension is still in great demand.

In this chapter, an efficient scheme is developed for classifying different hand movements from sEMG signals. The given sEMG signal is split into short duration sub-frames and then in each sub-frame autoregressive (AR) modeling is employed to extract reflection coefficients recursively from autocorrelation values. These coefficients are used as proposed features in kNN classifier, where hierarchical clustering (h.c) approach is followed. Classification into direct six class, namely total classification (t.c) had also been performed in order to select an optimum classifier. Extensive experimentation is carried out on a publicly available sEMG database to evaluate the classification performance of the proposed scheme under various conditions.

2.2 Database

The classification requires data of various basic hand actions that involves slow twitching and less motor unit firing. The database also needs to include both soft and tough actions of daily hand movements. The database used in this thesis is a freely available online database which was first launched at the 35th Annual International Conference of the IEEE EMBS at Osaka, Japan in 2013 by Christos Sapsanis, George Georgoulas, Anthony Tzes, and Dimitrios Lymberopoulos along with their thesis, "Improving EMG based Classification of basic hand movements using EMD" [9].

The database consists of the following six basic hand movements as shown in Figure 2.1:

a) Spherical: for holding spherical tools

b) Tip: for holding small tools

c) Palmar: for grasping with palm facing the object

d) Lateral: for holding thin, flat objects

e) Cylindrical: for holding cylindrical tools

f) Hook: for supporting a heavy load

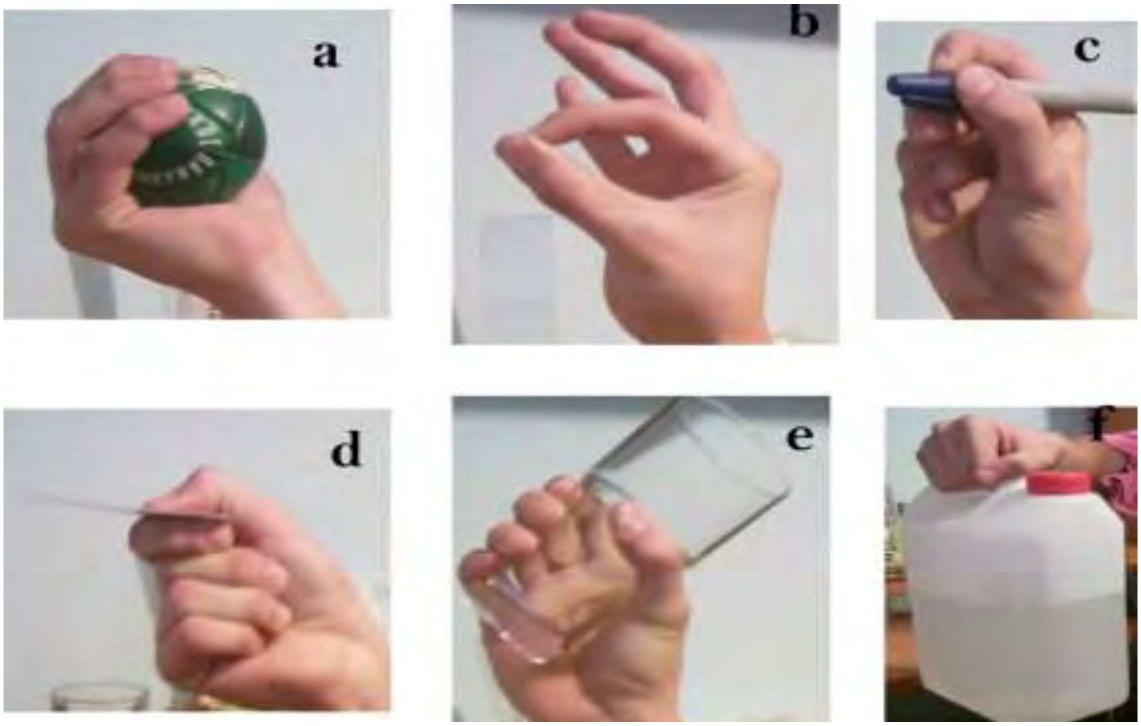

Figure 2.1: Illustration of the hand movement in the dataset: (a) Spherical, (b) Tip, (c) Palmar, (d) Lateral, (e) Cylindrical, (f) Hook. [9]

The dataset was collected from five healthy subjects (two males and three females) of the same age approximately (20 to 22 years old). The speed and force were intentionally left to the subject's will. For each movement the subject was asked to perform it for six seconds and the whole procedure was repeated 30 times for each basic movement. There were two forearm surface EMG electrodes (Flexor Capri Ulnaris and Extensor Capri Radialis, Longus and Brevis) held in place by elastic bands and the reference electrode in the middle, in order together information about the muscle activation. Therefore for each subject a total of 180 6-seconds long 2-channel EMG signals were recorded. The data were collected at a sampling rate of 500 Hz. Therefore, each action consists of 30 trials and for each trial the data contains 3000 samples.

The energy content in each trial for each of the five subjects (two males: m1 and m2) and three females: f1, f2 and f3) are analyzed independently for all six basic movements and shown in figures 2.2 to 2.7. It can easily observed that for a particular type of hand action, energy content significantly differs among various subjects, which indicates the toughness of the problem to be handled i.e. classification of different types of hand actions irrespective of the subjects.

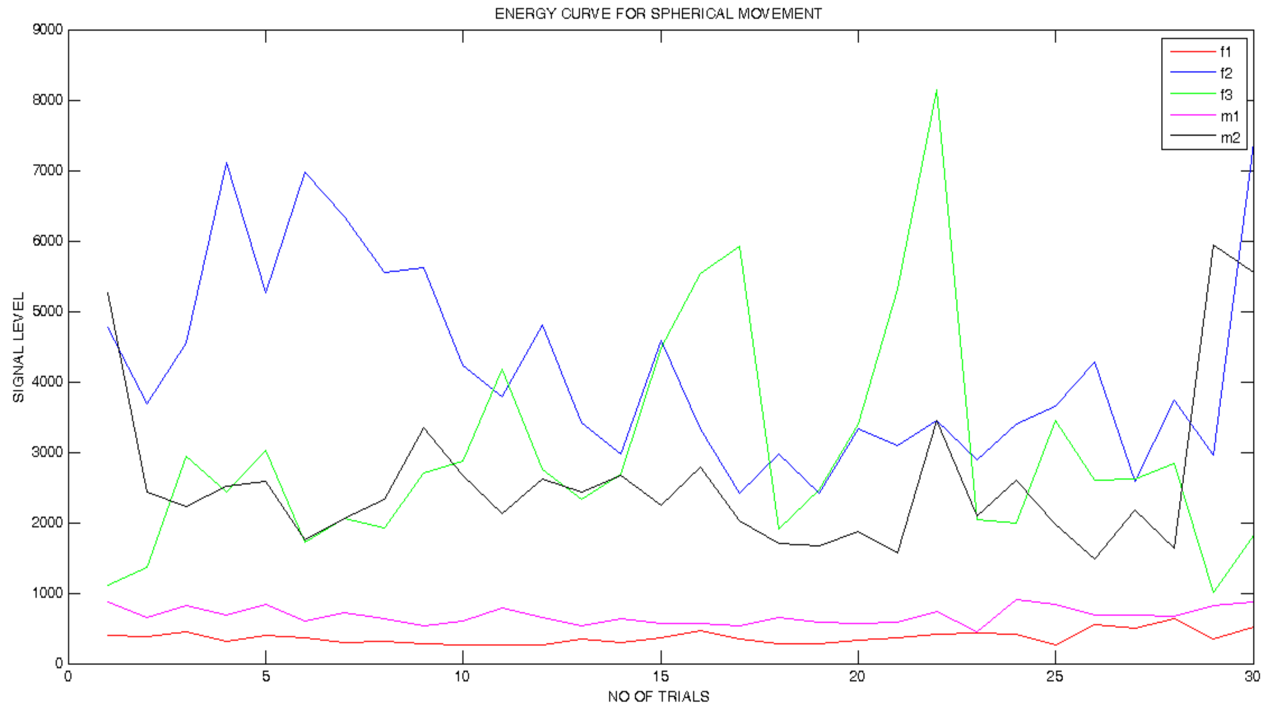

Figure 2.2: Energy Curve for Spherical Movement

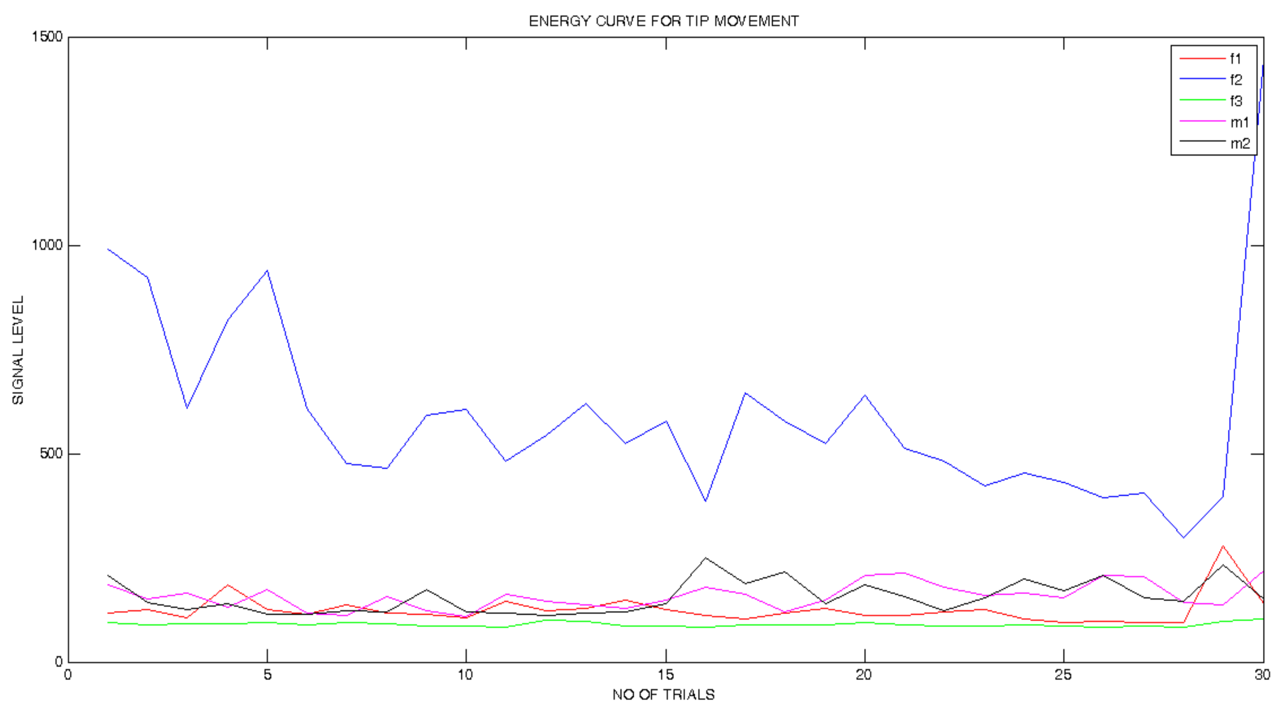

Figure 2.3: Energy Curve for Tip Movement

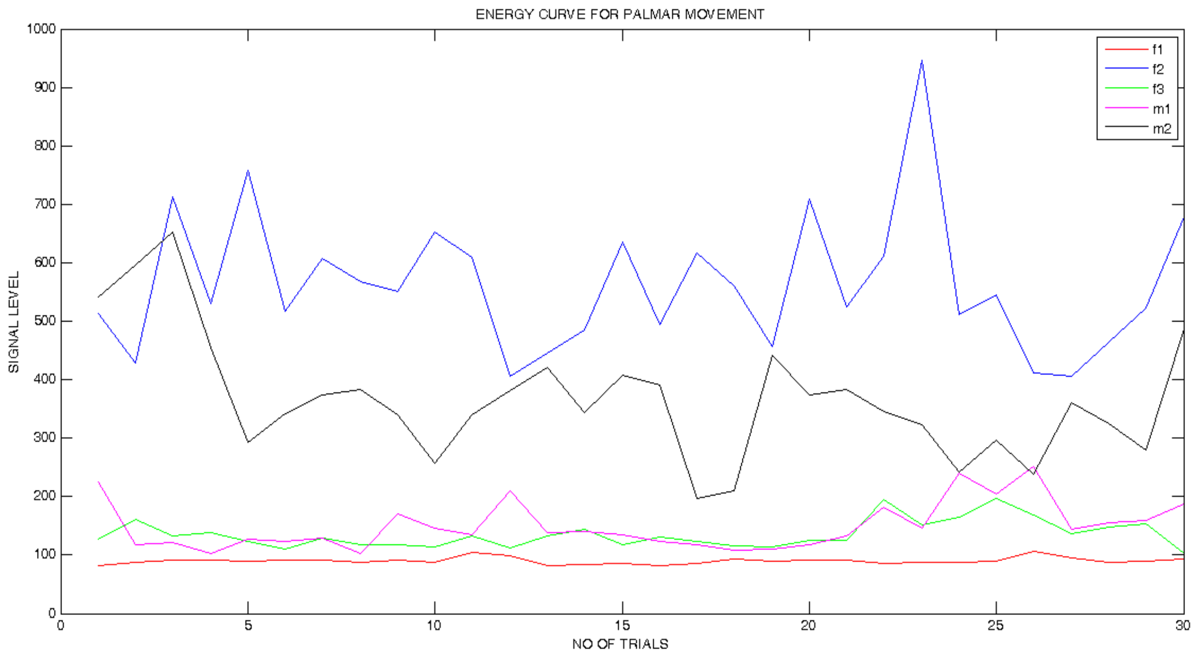

Figure 2.4: Energy Curve for Palmar Movement

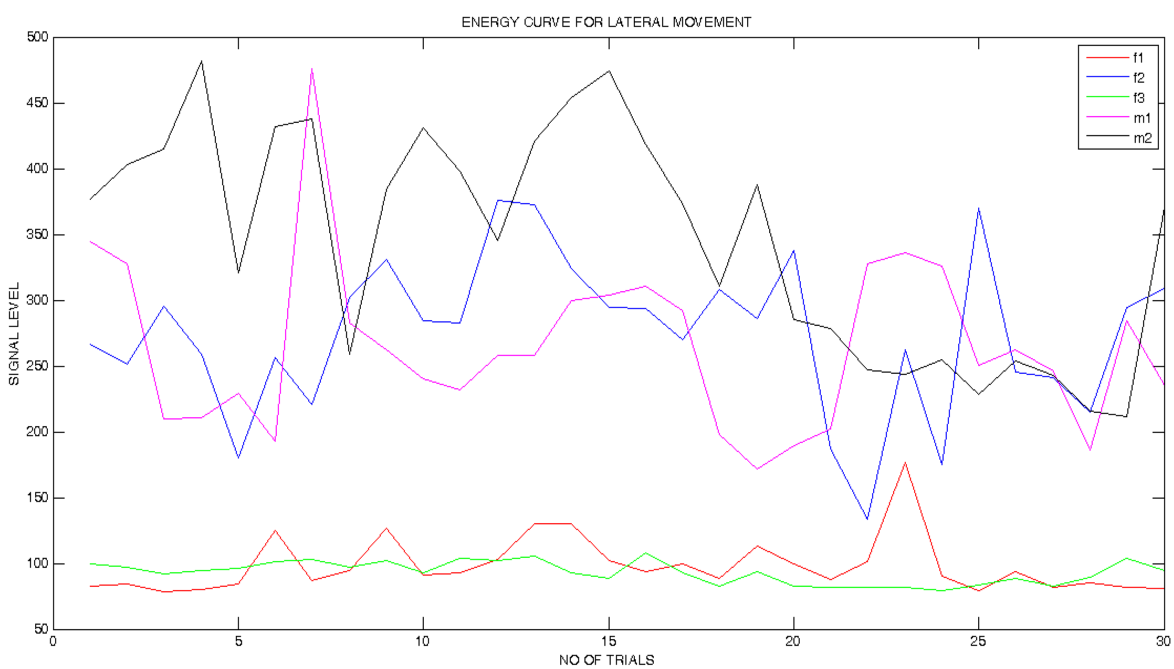

Figure 2.5: Energy Curve for Lateral Movement

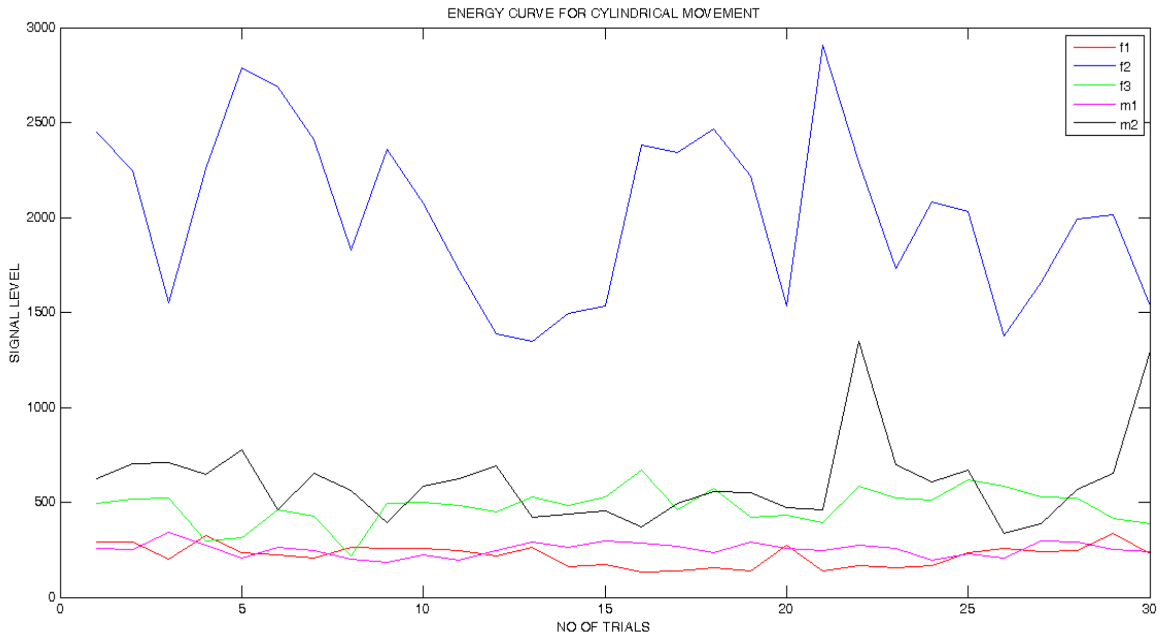

Figure 2.6: Energy Curve for Cylindrical Movement

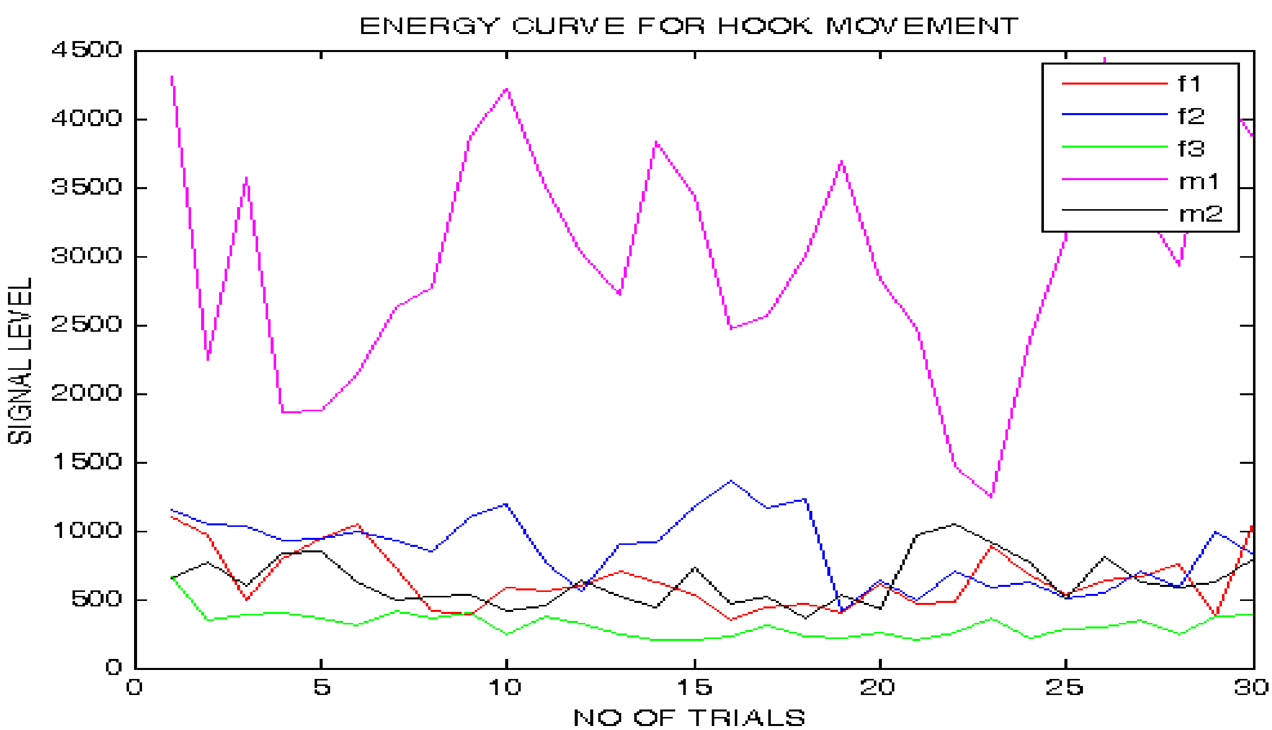

Figure 2.7: Energy Curve for Hook Movement

2.3 Proposed Method

The proposed method of hand movement recognition using sEMG signal is comprised of three stages: creating sub-frames in each frame of data, extracting features using AR parameter and kNN classification. A block diagram explaining the proposed Autoregressive Reflection (AR) Coefficient based autocorrelation function analysis method is presented in the following figure. The steps involved in the proposed method, which can also be found in the figure are discussed in details in the following sub-sections.

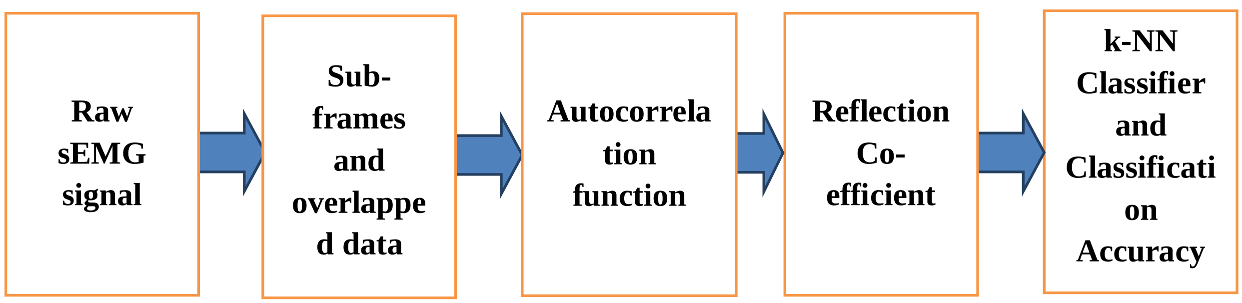

Figure 2.8: Block diagram explaining the Autoregressive Reflection Coefficient method.

2.3.1 Sub-Framing

Instead of considering the whole duration of the test data, we have divided each trial of the raw EMG signal into sub frames. Dividing the long data-set into short sub-frames ensures a constant local mean, which is a major advantage in estimation of consistent reflection coefficients by assuring stationarity of the data. Computation of reflection coefficients in each sub-frame reduce the effect of random fluctuation in the given test frame. Even if there is any inconsistency in a whole test frame, it will not have significant effect on the overall performance accuracy due to sub-framing. On the other hand, any short duration changes in the whole test frame will be reflected in the corresponding sub-frame based estimation. EMG data vary with time, the neural firings do not remain same throughout the whole six seconds and the applied stress levels also vary from beginning to end of any action. This variation pattern will also be different for different movements. Framing of the test data helps to capture these changes in terms of the extracted reflection coefficients. Here we have divided each trial of the test data of 3000 samples into an optimum number of 20 sub-frames, each having 150 samples. The sub-frame duration of the test data is an important factor. Too large a frame would have no additional advantage over taking the whole data-set, resulting non-stationary data with variable mean and non-consistent reflection coefficients. Again, if the sub-frame duration is too small, it may not contain any significant information that we want to extract from reflection coefficients. The optimum number of sub-frame is found to be 20 by experimentation.

2.3.2 Feature Extraction

A feature extraction scheme is proposed based on analysis of sub-framed EMG signal in order to perform the basic hand movement classification. Each sub-frame of 150 samples can be regarded as locally stationary. Each of these sub-framed data can be modeled as the output of a linear time invariant (LTI) autoregressive (AR) system [21] expressed as

$$x(n) = -\sum_{k=1}^{P}\left(a_k x(n-k) + u(n)\right) \tag{2.1}$$

Where u(n) is white Gaussian noise with a mean equal to zero and non-zero variance σ_u^2, $\{a_k\}$ are the AR parameters (generally referred to as linear prediction coefficients) and *x(n)* is the modeled output. Another point to be noted is that the AR system in question is causal. AR parameters have found extensive use as features in one-dimensional signal processing. Yule-Walker equations are employed to make an estimation of the AR parameters. These equations are given

$$\begin{aligned} r_x(m) &= -\sum_{k=1}^{p} a_k\, r_x(m-k) + \sigma_u^2 \delta(m), m \geq 0 \\ &= r_x(-m),\ m>0 \end{aligned} \tag{2.2}$$

Where $\delta(m)$ is the Kronecker delta function and $r_x(m)$, the autocorrelation function of $x(n)$ with length N, can be estimated as

$$r_x(m) = \frac{1}{N}\sum_{n=0}^{N-1-m} x(n)x(n+m), \qquad m \geq 0 \tag{2.3}$$

0, 1, 2,…, *P*. This will make matrix inversion compulsory, which may in turn end up being problematic considering the database in question. One other hurdle to be faced when using AR parameters as the only features during feature extraction is the significant variation in the values of the coefficients. Such variation in feature may lower the classification accuracy to a significant extent. With these obstacles in view, we have forgone the use of AR parameters as features. In lieu of AR parameters, we have opted for the use of reflection coefficients to distinguish the six basic hand movements. The i-th reflection coefficient (k_i) is in effect a measure of correlation between current output *x(n)* and i samples past output *x(n−i)* after having filtered the intermediary observations *x(n−1)* to *x(n−i+1)*. The reflection coefficients can be determined by making use of the following set of recursive equations for i = 1, 2,…, M.

$$\begin{aligned} k_i &= \frac{r_x(i) + \sum_{j=1}^{i-1} a_{i-1}(k) r_x(i-j)}{E_{i-1}} \\ a_i &= k_i \\ a_i &= a_{i-1} + k_i a_{i-1}(i-j), \quad 1 \leq j \leq (i-1) \\ E_i &= \left(1 - k_i^2\right) E_{i-1}, \quad i \geq 1 \end{aligned} \tag{2.4}$$

Here initially, $E_0 = r_x(0)$ and $a_0 = 0$. Keeping in view the disadvantages of using AR parameters to construct our feature set, utilizing reflection coefficients in this regard is the much better option. The points made below are some of the reasons why it is advantageous to use reflection coefficients for signal classification:

1. The absolute value of each reflection coefficient is less than 1 when the AR system is not unstable. As EMG signal is essentially the electrical activity of muscle and as it is safe to assume that EMG signal is locally stationary with the ability to be modeled as the output of a stable system, reflection coefficients will not exceed the value of 1. Such limitation in value is not achievable in the case of AR parameters seeing as their values differ from one another significantly.

2. EMG signals recorded in a laboratory setup are bound to get corrupted by different types of noise, especially if the equipment being used for signal extraction is of poor quality or if procedural mistakes are made. Reflection coefficients have much higher

immunity to noise than AR parameters. So using reflection coefficients as features to perform signal classification is the prudent course of action.

3. For slight differences in values of coefficients, reflection coefficients have the ability to render localization of spectral errors.

4. In order to determine reflection coefficients we do not have to go for the computationally expensive matrix inversion approach. Rather, a simple set of recursive equations afford us the required coefficients.

5. The reflection coefficients are determined iteratively by utilizing autocorrelation values. So increasing the number of reflection coefficients from P to P+1will provide us with simply one new coefficient; the rest of the coefficients will remain unchanged. On the contrary, increasing the AR model order by 1 will give us a completely new set of AR parameters.

Therefore, reflection coefficients can be used effectively to construct our feature vector for EMG signal classification. Another point of consideration, however, is the determination of the optimum model order for the database in question which will afford us with satisfactory classification accuracy. Here, the optimum number of reflection coefficients has to be chosen based on experimentation. In our case the best accuracy was obtained for an order of 20. Therefore, 20 reflection coefficients were obtained for each sub-frame, the mean of which are computed in order to reduce the feature dimension, thus each feature is converted from 20x20 to 20x1.

2.3.3 Classification

In the proposed method, classification was done by the k-nearest neighborhood (kNN) classifier. The kNN algorithm is a non-parametric method used in pattern recognition. For the purpose of classifying the hand movements, the value of k was set equal to 5. The classifier in question considers a distance function that is computed between the feature set of the test data and 5 neighboring patterns in the training data set. In the proposed method, classification is done using just the reflection coefficients obtained by fitting the EMG data to a twentieth order AR model. These coefficients are the only extracted features of the filtered EMG data and no additional statistical features need to be cascaded with these coefficients in order to perform the hand movement classification satisfactorily. Thus a lot of computational time can be saved. Here we have performed signal classification by adopting two different approaches. One approach constitutes the classification of the EMG signals into two different classes in the beginning, and then further classifying each class into three different classes, referred to as hierarchical classification (h.c). The second approach constitutes the direct classification of the signals into six different classes, namely total classification (t.c). It is observed that for the dataset used in this thesis, the first approach is more suitable as the classifier faces a relatively easier task at the beginning: two class problem with significant class separation. Three of the actions (cylindrical, hook and spherical) are far more forceful than the other three (palmar, lateral and tip). So, going ahead with two class classification and then classifying the members of these two classes into three different classes is expected to offer better classification performance.

2.4 Simulation Results

The performance of the above proposed method has been investigated by simulation in terms of classification accuracy. A brief overview of the major steps involved in the proposed method is presented with the help of a block diagram shown in figure 2.8. First the raw data is preprocessed where basically the overlapping sub-frames are constructed from the filtered data. Next the proposed feature, that is AR reflection coefficients are extracted using autocorrelation function. After feature extraction, the reflection coefficient vectors have been directly fed into kNN classifier. The features have been classified first into two classes and then three classes, referred to as hierarchical classification (h.c). Classification into direct six classes namely total classification (t.c) had also been performed in order to select an optimum classifier. In order to investigate the classification performance results obtained are shown in the Table 2.1.

Table 2.1 Comparison of Classification Accuracy Using Autoregressive Reflection Coefficient

Subject	**Percentage Accuracy (%)**		
	Proposed method h. c(Class 2 then class 3)	**Proposed method t. c (Direct Class 6)**	**[9]**
Female-1	94.333 (%)	89.556 (%)	85.24 (%)
Female-2	82.444 (%)	81.444 (%)	83.88 (%)
Female-3	97.778 (%)	97.889 (%)	84.82 (%)
Male-1	98.333 (%)	94.667 (%)	86.92 (%)
Male-2	96.444 (%)	95.000 (%)	92.38 (%)
Average Accuracy	93.8664 (%)	91.7112 (%)	86.65 (%)

Table 2.2 depicts the confusion matrix showing which hand movement is obtained in the output for corresponding input movement. For instance, in the fifth row of table II we can see that the lateral action is detected 28 times when the input action is lateral. However, the lateral action is erroneously detected as palmar once and it is also wrongly detected as tip once. These errors are not unexpected since these three actions can be categorized as actions requiring less force. So it is only to be expected that the lateral hand movement will not be confused with actions requiring greater force.

As mentioned before, only reflection coefficient of the AR parameters has been used as the feature for classification in comparison to eight features of the decomposed EMG signals mentioned in [9]. A major problem of AR modeling is to determine the model order appropriate for a given data. However, increasing the number of reflection coefficients by one means only one new coefficient is generated. This provides an opportunity to determine the optimum order which gives the maximum accuracy. Thus by means of iterative methods, an optimum order of 20 has been found to provide the highest accuracies as shown in the table above.

Table 2.2 Confusion Matrix for Female 2

Actions	Actions					
	Cylindrical	Hook	Spherical	Palmar	Lateral	Tip
Cylindrical	30	0	0	0	0	0
Hook	0	30	0	0	0	0
Spherical	0	0	30	0	0	0
Palmar	0	1	0	29	0	0
Lateral	0	0	0	1	28	1
Tip	0	0	0	0	3	27

Table 2.3 Confusion Matrix for Male 2

Actions	Actions					
	Cylindrical	Hook	Spherical	Palmar	Lateral	Tip
Cylindrical	30	0	0	0	0	0
Hook	0	30	0	0	0	0
Spherical	0	0	30	0	0	0
Palmar	0	0	0	30	0	0
Lateral	0	1	0	0	29	0
Tip	0	0	0	0	0	30

The effect of sub-framing the signals on the classification accuracy is also shown in the tables. In order to get a visual feel of how changing the order of the AR model affords us different results, we have plotted the variation of reflection coefficients corresponding to different trials for each action. Here only the effects of AR model of order 20 and 10 have been compared. But all orders less than 20 had been put to the test and the optimum order had ended up being 20. In Figure 2.9 we have shown how the sixth reflection coefficient (picked arbitrarily for the purpose of visualizing feature changes) varies for each action of female 1 when the AR model order is 20 and how the fourth reflection coefficient varies for each action of the same subject when the AR model order is 10. In Figure 2.10 feature variations have been depicted in the same manner but for female 2. In Figure 2.11 two plots are shown; in the first plot we have depicted how the eighth reflection coefficient varies with trial of each action of male 2 when the AR model order is 20 and in the second plot we have shown how the fourth reflection coefficient varies with trial for each action of the same subject when the AR model order is 10.

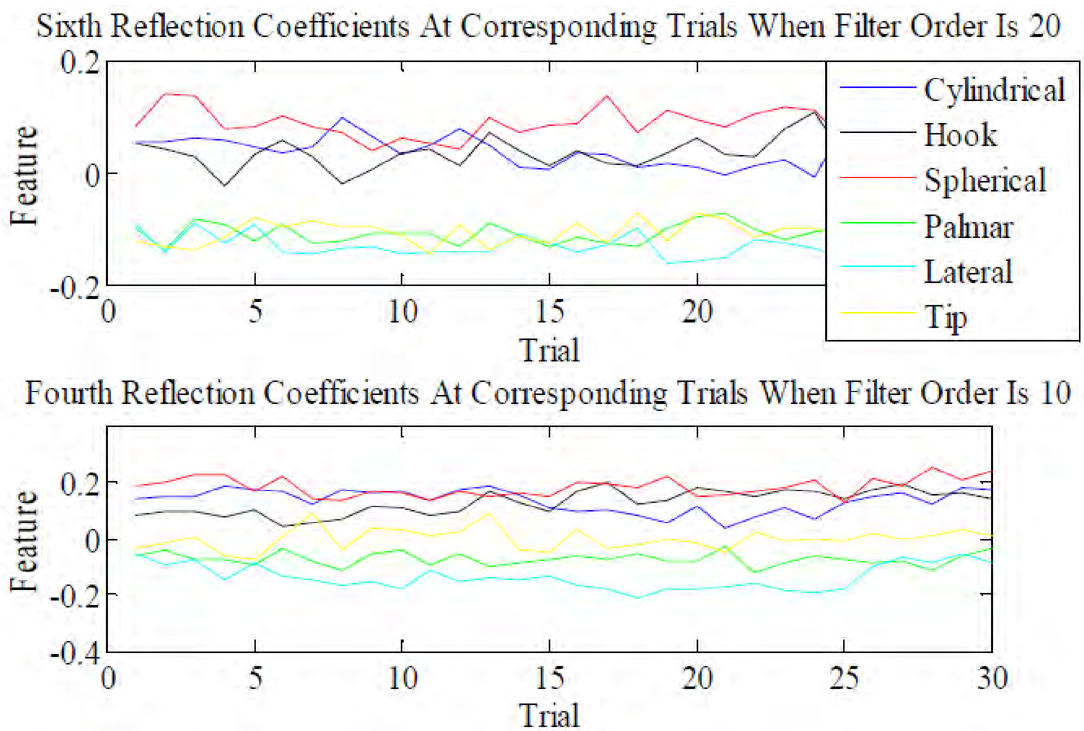

Figure 2.9: How reflection coefficient vary with trial in the case of each action of female 1 when filter order is 20 and when filter order is 10

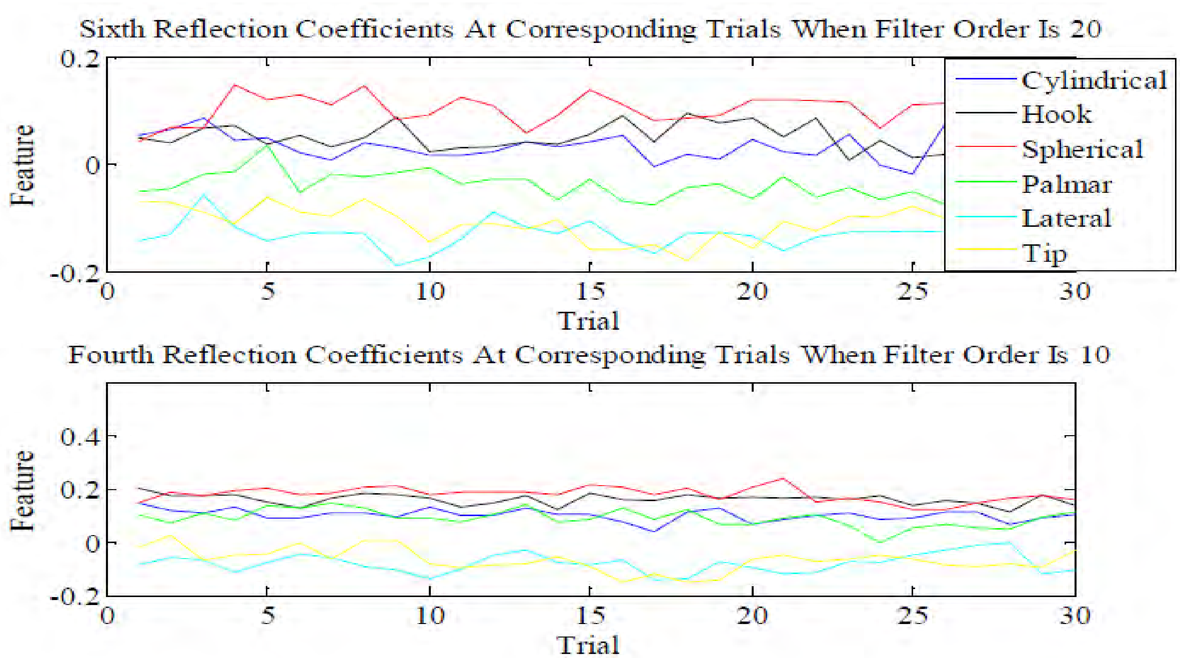

Figure 2.10: How reflection coefficient vary with trial in the case of each action of female 2 when filter order is 20 and when filter order is 10

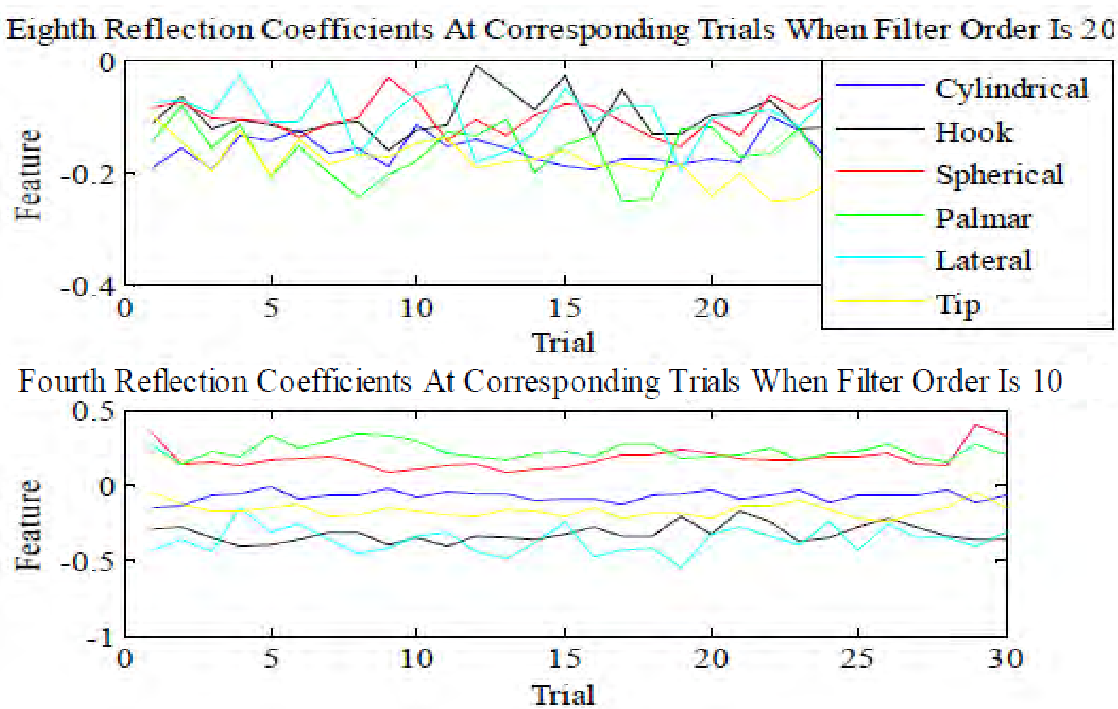

Figure 2.11: How reflection coefficient vary with trial in the case of each action of male 2 when filter order is 20 and when filter order is 10

Figure 2.9, Figure 2.10 and Figure 2.11 prove that the actions are more distinguishable when the AR model order is 20. When the order is less than 20, the six actions of a particular subject lose their distinguish ability to a considerable extent. The variation of accuracy for different AR model order for male 2 is depicted in Figure. 2.12. It can be inferred from the figure that the optimum number of reflection coefficients that affords the best classification accuracy is 20. Also, it is seen from Fig. 2.13 that order 20 is the optimum AR order for which satisfactory classification accuracy can be achieved for all five subjects.

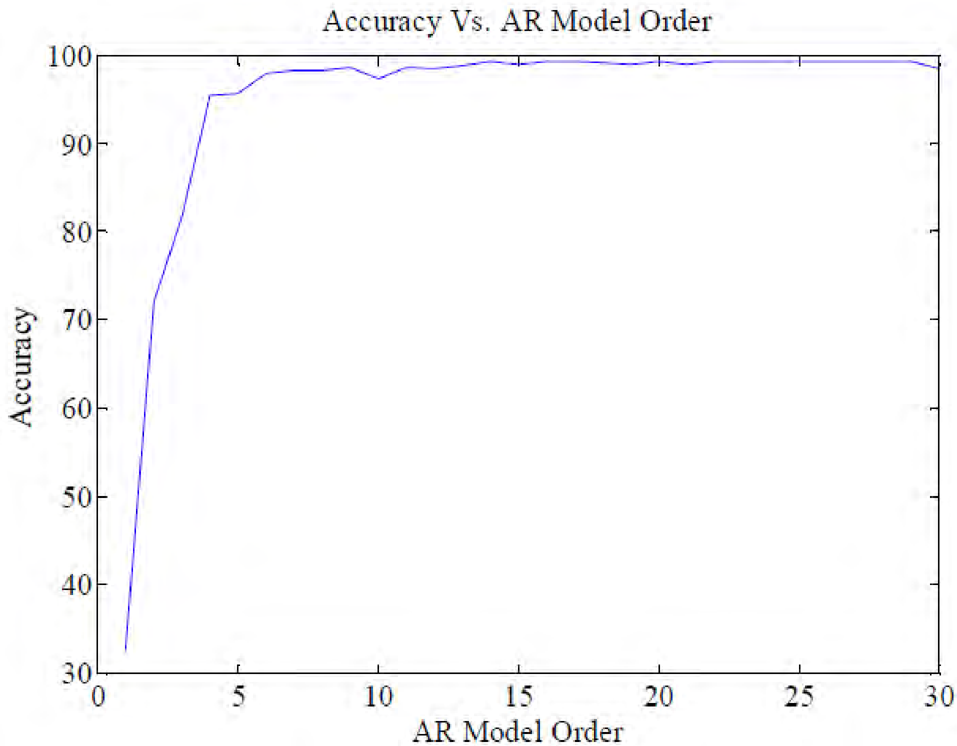

Figure 2.12: How accuracy varies for different AR model order for male 2

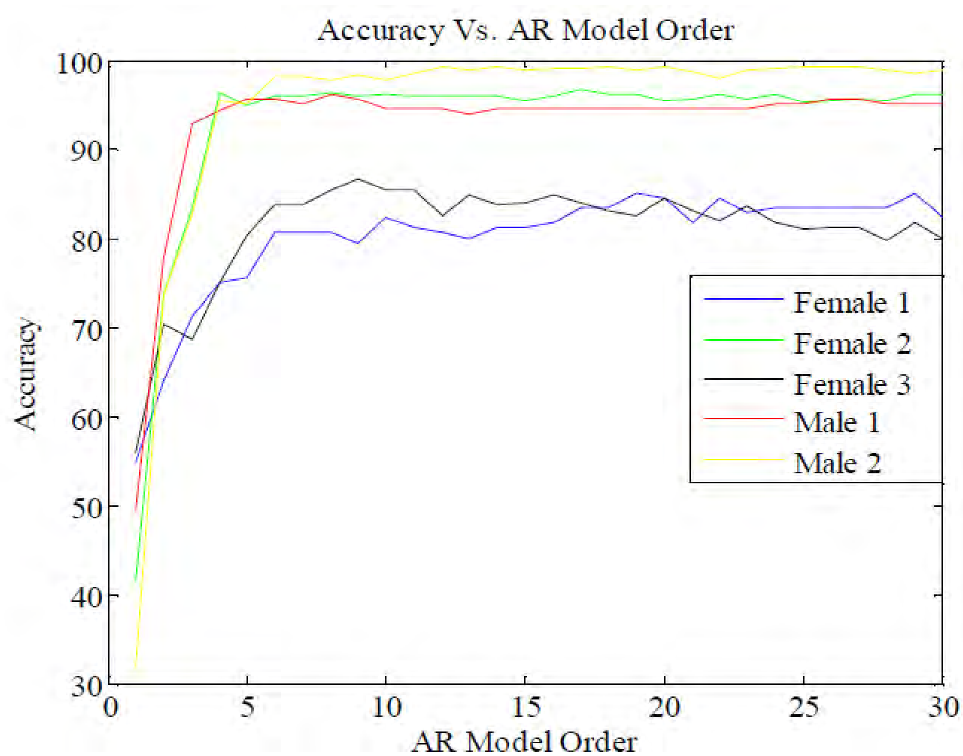

Figure 2.13. How accuracy varies for different AR model order for all five subjects

2.5 Conclusion

For the classification of six basic hand movements, it is observed that reflection coefficients offer quite satisfactory feature quality when the AR model order is chosen relatively higher, such as 20 due to wide spectral characteristics of sEMG signal. The hand movements can easily be divided into two classes depending on number of neural firing and motor unit engagement. This difference in biomedical phenomena is clearly reflected in the proposed feature vectors; especially the six types of movements can easily be classified into two types and each of these two types can be further classified. Hence, hierarchical kNN classification is proposed to obtain better performance. Instead of extracting the feature considering the entire frame, sub-frames are created and then AR reflection coefficients are computed on each of those sub-frames. Finally the average of the extracted reflection coefficients is considered as feature. Conventional techniques involve computation of several statistical features. However, the advantage of the proposed method is that it only requires computation of reflection coefficients which can provide consistently high classification accuracy. But the study in question is limited to just six basic hand movements. It remains to be seen how well the proposed method holds up in the case of a greater number of hand actions. Further development of our proposed method can surely contribute in the sector of prosthetic arms development and even in the classification of various neuromuscular diseases.

Chapter 3

Hand Movement Recognition Using Singular Value Decomposition of Surface EMG Signal

3.1 Introduction

Electromyography (EMG) is a representation of electrical activity of muscle cells, which originates in response to a nerve's stimulation. It can either be obtained via needle or via surface electrodes (sEMG). The use of sEMG is of great interest to researchers because of its non-invasive acquisition technique and now-a-days it is being extensively used in various applications, such as prosthetics development, identification and classification of several neuromuscular diseases, muscle injury identification, and rehabilitation. Prosthetic arms provide a new lease on life to the people who have had to be amputated [22]. Unlike electroencephalogram (EEG), the myoelectric prosthetic arm is easier to manipulate. It makes use of the EMG signals from the patient's organs and manipulates movement of the prosthetic arm [17]. Success in classifying acquired sEMG signal influences the degree of effectiveness of control strategies of a robotic hand with advancements in biosensors, pattern identification and biological signal processing. Hand movement recognition has been looked into in the past by several scholars and they had used complicated and time consuming techniques of signal decomposition and extraction of quite a few features from the decomposed signals. By decomposing the sEMG signals via empirical mode decomposition (EMD) and then obtaining features from the EMD decomposed signals, different hand movements are classified with the help of the linear discriminant analysis [9]. Some commonly used measures used as features are zero-crossing, slope sign change, waveform length, Willison amplitude, integrated EMG, variance, kurtosis and skewness [9],[11]. In [15], two-channel sEMG signals are classified via a linear kernel support vector machine (SVM). In [8], four hand actions are differentiated employing various time domain features. It is observed from these studies that due to noise like characteristics of sEMG signals, poor classification accuracy may be obtained for similar types of movements. A straightforward yet effective feature extraction technique that results in relatively acceptable classification performance with a reasonably small feature dimension is yet to be put forth.

In this chapter, an effective scheme is brought to light for the purpose of identifying different hand movements from sEMG signals. A frame of sEMG signal is divided into overlapping sub-frames and then singular value decomposition is applied. The singular value decomposed data are then used for AR analysis and obtaining reflection coefficients. The average values of the AR reflection coefficients obtained from different sub-frames are proposed as features to be used by the k nearest neighbor (kNN) classifier to perform the classification. Experimentation is carried out on the same sEMG database mentioned in the previous chapter to examine the classification accuracy of the technique put forward here under several different conditions.

3.2 Proposed Method

The proposed method of hand movement recognition using sEMG signal is comprised of three stages: creating sub-frames in each frame of data, extracting features using the SVD based AR analysis and kNN classification. A block diagram explaining the proposed SVD based AR analysis method is presented in the following figure. The steps involved in the proposed method, which can also be found in the figure are discussed in details in the following sub-sections.

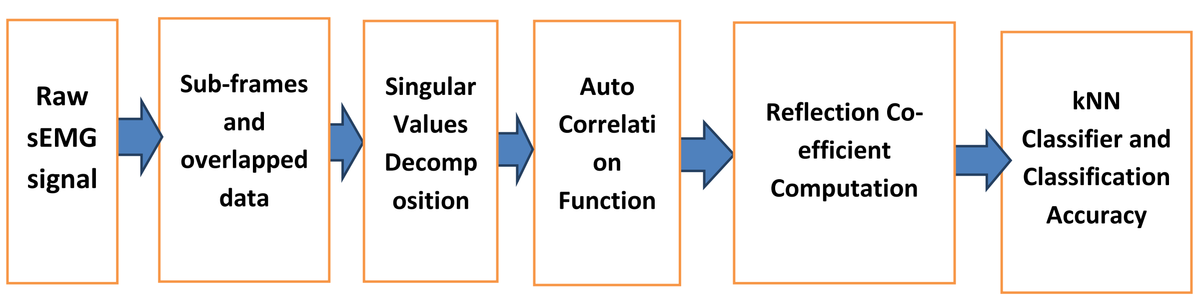

Figure 3.1: Block diagram explaining the proposed SVD based method.

3.2.1 Sub-Framing

Instead of working on the entire duration of the sEMG signals, we have first created several sub-frames from each sEMG signal. Obtaining short sub-frames from each trial of sEMG signal removes the possibility of inconsistency in the computation of singular values to a considerable extent by assuring stationarity of the data. Even if there are any inconsistencies present in the whole test data, it will not noticeably affect the overall classification accuracy owing to the fact that we are working with short duration sub-frames. On the contrary, any short duration fluctuations in the whole test data due to hand movement variation will be reflected in the corresponding sub-frame based estimation. sEMG data generally change with time; the neural firings keep changing throughout the whole six seconds and the applied pressures also do not remain constant from the beginning to the end of any action. The pattern of the changes will also be different for different hand actions. Sub-framing of the sEMG signals helps to identify these changes indirectly through changing singular values feature.

Each trial of the test data is divided into overlapping sub-frames. The length of the sub-frame and overlaps are chosen in such a way that the SVD can be performed. The overlapping nature of the sub-frames ensures smooth variation of the features across the sub-frames. The sub-frame duration is an important factor as the SVD is to be employed. Too large a frame would have no additional advantage over taking the whole data-set, resulting nonstationary data with variable mean and nonconsistent features. Again, if the sub-frame duration is too small, it may not contain any significant information and will be very difficult to carry out SVD analysis.

3.2.2 Feature Extraction

A feature extraction scheme is proposed based on analysis of sEMG signal with a view to performing hand movement classification. From a given frame of sEMG data, some overlapping sub-frames are extracted and it is ensured that each sub-frame contains reasonably small number of samples. The reason behind considering the small duration of sub-frames is to extract precisely the local variation of motor unit action potentials (MUAPs) due to various hand actions. If large duration frames or sub-frames are taken, one may expect less consistency in the behavior of MUAPs. Moreover, a very small time shift is preferred to increase the chance of getting more sub-frames that are capable of capturing the entire characteristics of muscle firing. In general, sEMG data are very noisy unlike needle EMG signals. In order to exclusively observe the behavior of MUAPs due to various hand actions, it is desirable to design a feature extraction algorithm which is immune to noise or which can extract features after reducing the effect of noise. One possible way that is proposed in this thesis is to construct sub-frames of sEMG data with overlapping between sub-frames assuming that a very small time shift is chosen while creating the sub-frames. The singular value decomposition (SVD) algorithm is well known for its application in noisy data. The noise in sEMG data can be considered to be an unwanted signal with small but randomly changing amplitude added to the signal we want to work with. Singular value decomposition (SVD) expresses an m-by-n matrix X can be written as

$$\mathbf{X = U*S*V'}$$

Here, S is an m-by-n diagonal matrix with singular values of X on its diagonal. The columns of the m-by-m matrix U are the left singular vectors for corresponding singular values. The columns of the n-by-n matrix V are the right singular vectors for corresponding singular values. V' is the Hermitian transpose (the complex conjugate of the transpose) of V. We have opted SVD by using widely acceptable matlab built-in function. It is expected that the singular values are very much distinguishable for different actions and can provide better features. The Figure.3.1 shows the sub-frame signal versus SVD signal.

After performing the SVD on each sub-frame of sEMG data, on the resulting singular value decomposed data, AR analysis is carried out to extract AR reflection coefficients in a similar way as presented in Section 2.3.2. From the extracted sub-frame based AR reflection coefficients, an averaging is performed to construct the final feature vector, which depends on the order of the AR model.

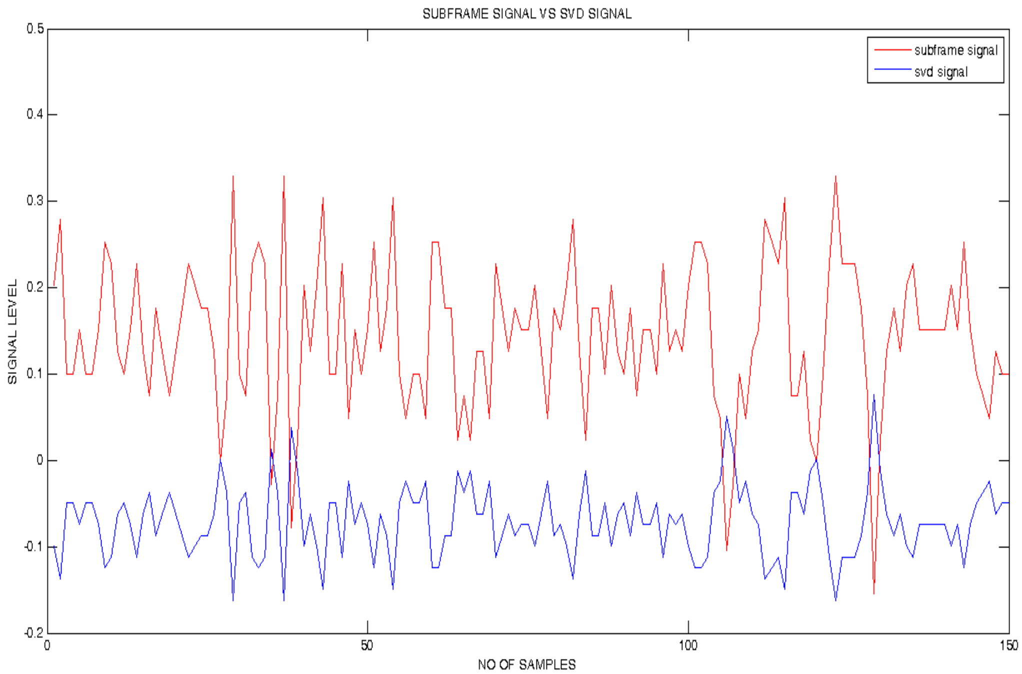

Figure 3.2: Sub-frame signal versus SVD signal

3.2.3 Classification

In our proposed method, classification was performed by the K-nearest neighborhood (kNN) classifier. The K-nearest neighbor algorithm is a non-parametric method widely employed in pattern recognition. In order to perform the classification of the hand movements in question, the value of K was set equal to 5. The kNN classifier happens to consider a distance function [1] that is determined between the feature vector of the test data and the training data set.

3.3 Simulation Result

In the method put forward here, classification is performed using the mean AR reflection coefficient features obtained from the singular values of the sub-frames of sEMG signal. Each trial (or frame) of the test data consists of 3000 samples and we divide the frame into an optimum number of 20 sub-frames, each having 150 samples, which is found suitable for employing SVD. The mean AR reflection coefficients are the only extracted features of the sub-frames generated from a frame of sEMG data and no additional statistical features need to be added to these parameters obtained via singular value decomposition in order to perform the hand movement classification. In this way a great deal of computational time can be saved.

The performance of the method proposed above has been examined via simulation with regards to classification performance. Right after feature extraction, the feature vector comprised of mean AR reflection coefficient extracted from the singular values of the sub-frames has been directly used in the kNN classifier to perform the classification. The features have been categorized first into two classes and then three class (h.c). Classification into direct six classes (t.c) had also been performed, but it is found from the accuracies that the former method provides comparatively better accuracy. The comparative performance analysis is shown in the Table 3.1.

Table 3.1 COMPARISON OF CLASSIFICATION ACCURACY USING SINGULAR VALUES DECOMPOSITION

Subject	**Percentage Accuracy (%)**		
	Proposed method h. c (Class 2 then class 3)	**Proposed method t. c (Direct Class 6)**	**[9]**
Female-1	94.333 (%)	90.667 (%)	85.24 (%)
Female-2	80.556 (%)	80.667 (%)	83.88 (%)
Female-3	98.889 (%)	97.889 (%)	84.82 (%)
Male-1	97.778 (%)	95.333 (%)	86.92 (%)
Male-2	96.889 (%)	96.222 (%)	92.38 (%)
Average accuracy	94.333 (%)	90.667 (%)	86.65 (%)

This is because three of the actions in the database we are working require greater force (cylindrical, hook and spherical) and the rest three do not require a great amount of force (palmar, lateral and tip). As such it stands to reason that first identifying whether the action being classified is a more forceful action or not will ultimately ensure greater classification accuracy. The last column of Table 3.1 contains the classification accuracy obtained via the method proposed in [9]. But in order to make a fair comparison kNN classifier has been used to implement the method of [9] in lieu of LDA classifier with the value of K being 5 in all the cases.

The confusion matrix shown in Table 3.2 depicts which hand movement is obtained in the output for corresponding input movement for Male 2.

Table 3.2 CONFUSION MATRIX FOR MALE 2

Actions	**Actions**					
	Cylindrical	Hook	Spherical	Palmar	Lateral	Tip
Cylindrical	28	0	2	0	0	0
Hook	0	30	0	0	0	0
Spherical	2	0	28	0	0	0
Palmar	0	0	0	28	0	2
Lateral	0	0	0	1	21	8
Tip	0	0	0	2	1	27

Table 3.3 CONFUSION MATRIX FOR FEMALE 1

Actions	**Actions**					
	Cylindrical	Hook	Spherical	Palmar	Lateral	Tip
Cylindrical	22	8	0	2	0	0
Hook	10	17	3	0	0	0
Spherical	1	4	25	0	0	0
Palmar	0	0	0	28	2	0
Lateral	0	1	0	1	28	1
Tip	0	0	0	2	1	29

For instance, in the fifth row of Table 3.2 we can see that the lateral action is detected 21 times when the input action is lateral. However, the lateral action is erroneously detected as palmar once and as tip no less than 8 times. These mistakes made by the classifier can be justified seeing as these three actions are movements associated with a lower amount of force. Therefore it is quite natural that the lateral hand movement will not be mistaken for actions associated with greater force. In the same way, in the sixth row of Table 3.2 it can be observed that the tip action is recognized as itself twenty-seven times. But twice the classifier has been misled to believe that the tip action is the palmar hand movement and once the tip action is wrongly detected as the lateral hand movement. As the palmar, lateral and tip actions belong to the category of less forceful hand actions, such error is really not surprising. We can think that movements requiring force of a similar range have similar neural firing. Therefore it can be said that the sEMG signals of the database in question can be easily differentiated into two separate categories on the basis of corresponding neural firing. The confusion matrix depicted in Table 3.3 is exactly the same as that of Table 3.2 except that it represents how input and output vary for Female 1. As can be inferred from observing the tables, the classification accuracy for Male 2 is higher than that of Female 1, which is consistent with our findings presented in Table 3.1.

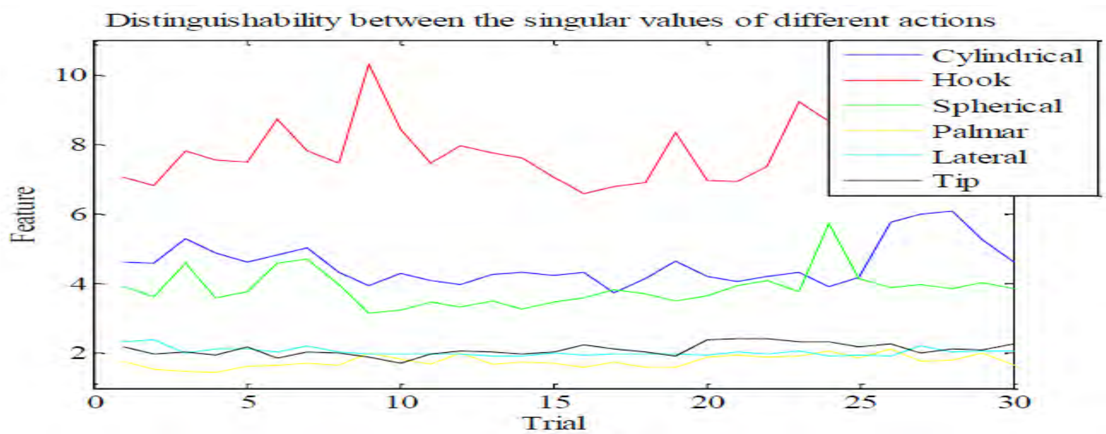

Figure 3.3: How energies vary with singular values of trials in the case of each action of Male 1

Only mean AR reflection coefficients have been used as the features for classification in comparison to the eight features of the decomposed EMG signals mentioned in [9]. Here, we have divided an entire frame of data into overlapping sub-frames and then SVD is performed. This approach requires optimum selection of sub-frame duration and also optimum number of sub-frames. Sub-frame duration of 150 samples has been found suitable to provide better accuracies as shown in the tables above. The classification accuracy for each subject computed by our proposed method is compared with the classification accuracy computed with the method proposed in [9] in Table 3.1.

In order to visualize how distinguish ability between the energies in singular values of different actions, we have plotted the variation of energies in singular values corresponding to different trials of each action of the same subject (Male 1) in figure 3.3 considering 20 sub-frames. As can be seen quite clearly from figure 3.3, distinction among the actions can be made more easily. A similar analysis is shown in figure 3.4 for female 2. As we can see, the distinguish ability between the singular values is quite high. So, singular values were used to compute AR reflection coefficients. The variation of accuracy for different sub-frame durations for Female 2 and Male 1 are depicted in figure 3.5 and figure 3.6, respectively. Similar graphs for the other three subjects are achieved for all five subjects.

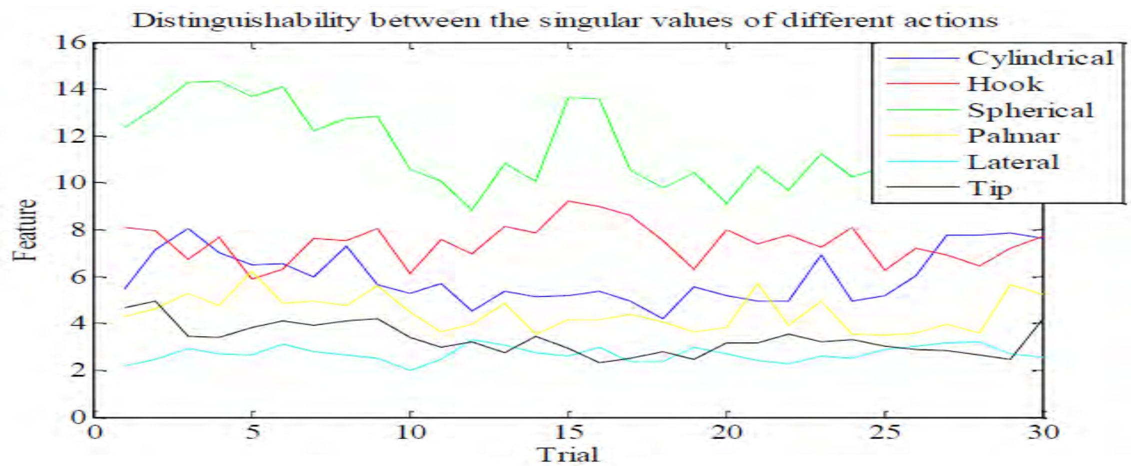

Figure 3.4: How energies vary with singular values of trials in the case of each action of Female 2 when sub-frame is 20

From figure 3.5 and figure 3.6, it can be observed that 300 ms duration for a sub-frame can be chosen with satisfactory performance. The reason why we get high classification accuracy taking short sub-frames is that each trial of each sEMG signal representing an action is made up of several Motor Unit Action Potentials (MUAPs). Neural firing of muscle cells are the reason these MUAPs originate. It stands to reason each MUAP of a particular action will have characteristics distinct from the other constituent MUAPs. As neural firing of muscles occurs for an infinitesimally short duration we have opted for short duration sub-frames.

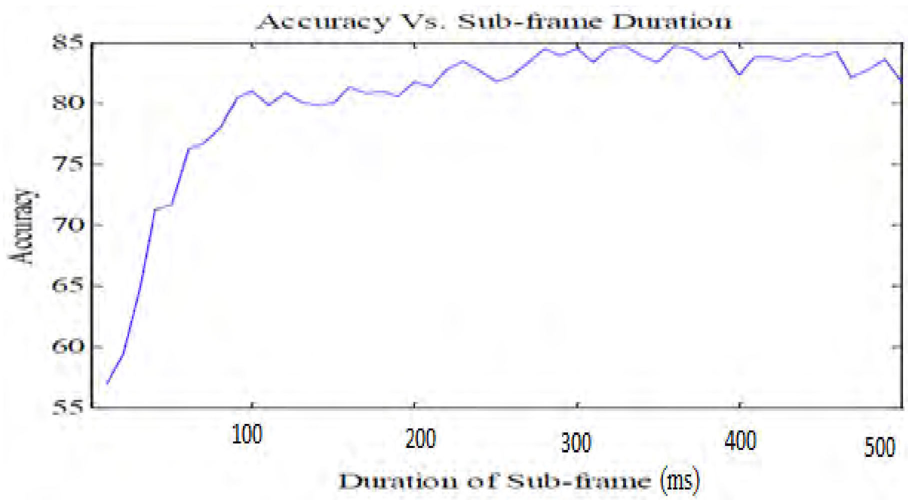

Figure 3.5: How accuracy happens to vary for different sub-frame duration in case of Female 2

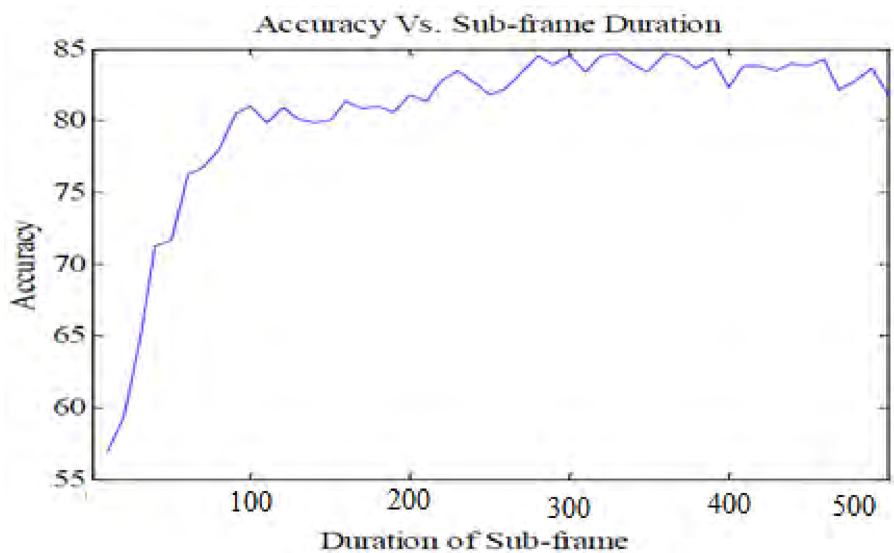

Figure 3.6: How accuracy happens to vary for different sub-frame duration in the case of Male 1

The study that has been conducted here is a contribution to the sector of prosthetic arms development. Amputees can gradually go back to leading normal lives if they are provided with successfully developed prosthetic arms. These arms detect the sEMG generated by the undamaged nerve cells and in response to the nerve activity these arms perform the tasks that the patient wants accomplished. The alternate approaches to prosthetic arms development are brain controlled prosthetic arm and voice controlled prosthetic arm. However, it should be kept in mind that the EEG signals (representations of the electrical activity of the brain) are exceedingly weak. On top of that they are quite noisy and additionally EEG sensors are quite expensive. As for voice regulated arms, they will disrupt the normal conversational flow of the patient. A cheaper and more convenient approach, therefore, is the use of sEMG signals in order to control the prosthetic arm. Furthermore, our study can also contribute to the detection and classification of various neuromuscular diseases minor ones like muscle fatigue or even major ones like Parkinson's. It is indisputable that sEMG signals are different in a healthy subject and a subject suffering from a neuromuscular disease or disorder.

3.4 Conclusion

For the classification of hand movements, it is observed that the features provide satisfactory feature quality when the number of sub-frames is 20. The hand movements can be categorized into two classes depending on number of neural firing and motor unit engagement. This difference in biomedical phenomena is clearly reflected in the proposed feature vector. The six types of movements can easily be classified into two types and each of these two types can be further classified into three types. Hence, hierarchical kNN classification is proposed to obtain better results. Instead of extracting the feature considering the entire frame, sub-frames are created and then singular values are computed from each of those sub-frame matrices. Finally these singular values along with the mean are considered as features. Conventional techniques involve computation of several statistical features [9]. However, the advantage of the proposed method is that it requires computation of features which can provide consistently higher classification accuracy than the results obtained in [9]. But the study in question is limited to just six basic hand movements. It remains to be seen how well the proposed method holds up in the case of a greater number of hand actions. Further development of our proposed method can surely contribute in the sector of prosthetic arms development and even in the classification of various neuromuscular diseases.

Chapter 4

Hand Movement Recognition Using Discrete Wavelet Transform of Surface EMG Signal

4.1 Introduction

Electromyography (EMG) refers to the collective electric signals from muscles, which is controlled by the nervous system and produced during muscle contraction. The signal represents the anatomical and physiological properties of muscles; in fact, an EMG signal is the electrical activity of a muscle's motor units. EMG signal has a variety of clinical and biomedical applications. EMG is used as a diagnostics tool for identifying neuromuscular diseases, or to detect level of muscle fatigue, and disorders of motor control. EMG signals are also used as a control signal for prosthetic devices, such as prosthetic hands, arms and lower limbs [16]- [17]. There are two kinds of EMG: surface EMG (sEMG) and needle EMG (nEMG). Surface EMG assesses muscle function by recording muscle activity from the surface above the muscle on the skin. Needle EMG is recorded using needle electrode inserted into a muscle for exact detection of the signal from contracted muscle. Needle EMG is an invasive process, thus is not applicable for purposes other than disease detection. On the other hand surface EMG is non-invasive and can be simply recorded from above the surface of the skin. As a result widespread potential applications for surface EMG signal classification and control have been reported in the last two decades including multifunction prosthesis, electrical wheelchairs, virtual mouse and keyboard, and virtual worlds. Surface EMG can be recorded by a pair of electrodes or by a more complex array of multiple electrodes. More than one electrode is needed because EMG recordings display the potential difference (voltage difference) between two separate electrodes. But working with surface EMG brings about some challenges due to the fact that surface electrode recordings are restricted to superficial muscles, are influenced by the depth of the subcutaneous tissue at the site of the recording which can be highly variable depending of the weight of a patient, and cannot reliably discriminate between the discharges of adjacent muscles. For the identification of motion command from sEMG signals, different approaches have been suggested where typical neuromuscular tasks and a large number of electrodes are considered [3]. In [6], four neuromuscular tasks are differentiated employing various time domain features. By decomposing the sEMG signals via empirical mode decomposition (EMD) and then obtaining features from the EMD decomposed signals, different hand movements are classified with the help of the linear discriminant analysis [9]. Some commonly used features are zero-crossing, waveform length, Willison amplitude, and integrated EMG [9]-[11]. Frequency domain analysis is also performed to classify sEMG signal [12]-[14]. In [15], six wrist motions are classified utilizing wavelet decomposition on the entire frame and linear kernel support vector machine (SVM) classifier. It is observed from these studies that due to noise like characteristics of sEMG signals, poor classification accuracy may be obtained for similar types of neuromuscular actions. To overcome the problem, in many cases, a very high feature dimension is used. An efficient scheme of extracting features from decomposed subframe of sEMG signal, which offers very satisfactory classification performance with low feature dimension is still in great demand.

In this thesis, we propose an EMG based basic hand movement detection using discrete wavelet transform (DWT) data and unlike previous proposed methods, extracted the reflection coefficients from the DWT of sEMG data for features. The goal is to develop efficient classification scheme to detect various types of hand movements where six classes of movements are to be classified. Wavelet coefficients were extracted from preprocessed raw EMG data. Then autoregressive reflection coefficients were calculated. The kNN classifier was used to recognize the signal of different movement classes from features extracted from wavelet coefficients. This method increases the classification accuracy as well as reduces the computational time as only one feature set is used.

4.2 Proposed Method

The method proposed in this chapter for the classification of basic hand movements using surface EMG constitutes the following steps: sub framing of the surface EMG signal, feature extraction and classification. A block diagram explaining the proposed method is presented in the following figure. The steps involved in the proposed method, which can also be found in the figure are discussed in details in the following section.

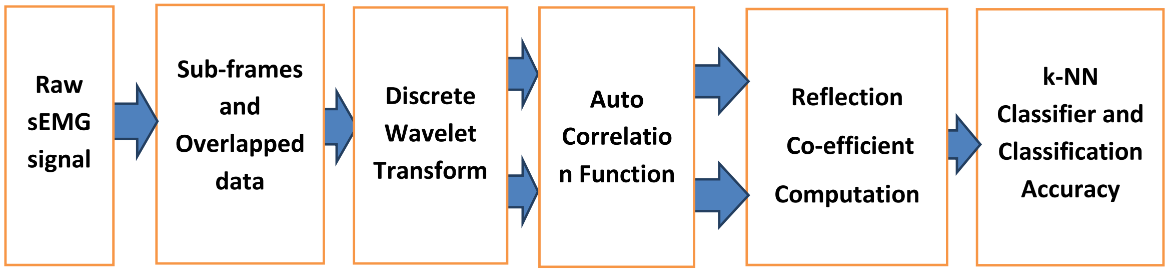

Figure 4.1: Block diagram explaining the proposed DWT based method

4.2.1 Sub-Framing

Instead of considering the whole duration of the test data, we have divided each trial of the raw EMG signal into sub frames. Dividing the long data-set into short sub-frames ensures a constant local mean, which plays a major role in applying the DWT followed by AR analysis assuring stationarity of the data. Computation of DWT based features in each sub-frame, instead of computing in the whole frame, reduces the effect of random fluctuation in the given test frame. Even if there is any inconsistency in a whole test frame, it will not have significant effect on the overall performance accuracy due to sub-framing. On the other hand, any short duration changes in the whole test frame will be reflected in the corresponding sub-frame based estimation.

EMG data vary with time, the neural firings do not remain same throughout the whole six seconds and the applied stress levels also vary from beginning to end of any action. This variation pattern will also be different for different movements. Framing of the test data helps to capture these changes in the DWT coefficients and consequently in AR analysis on those coefficients. Here we have divided each trial of the test data of 3000 samples into an optimum number of 20 sub-frames, each having 150 samples, which is found suitable for employing DWT. The sub-frame duration of the test data is an important factor as the DWT is to be employed. Too large a frame would have no additional advantage over taking the whole data-set, resulting nonstationary data with variable mean and nonconsistent coefficients. Again, if the sub-frame duration is too small, it may not contain any significant information and will be very difficult to employ the DWT. The optimum number of sub-frame is found to be 20 by experimentation. Since our target is to focus on each of the points in the signal where muscle is

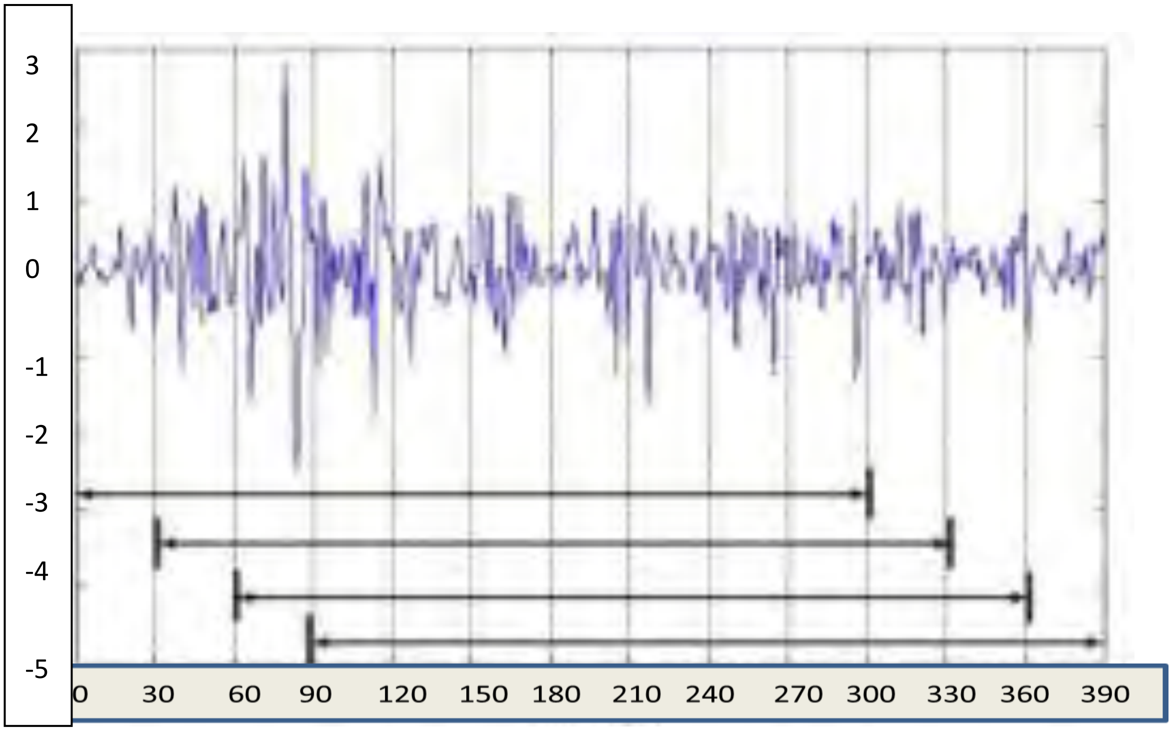

Figure 4.2: 300 msec long overlapping windows to compute the DWT

contracted, in this work we selected the overlapping approach with time windows of 300 msecs (150 data points) and an overlap of 270 msecs (or a time leap of 30 msecs) which is shown in Figure 4.2.

4.2.2 DWT Based Feature Extraction

The DWT is a multi-resolution technique that offers localization both in time and frequency [25]–[30]. It exhibits good frequency resolution at low frequencies and good time resolution at high frequencies. Moreover, it offers the advantages of low computational cost and ease of implementation. Hence, the DWT is chosen to extract features from the EMG signal. The DWT of a signal $x[n]$ can be obtained as

$$C(a,b) = \sum_{n\epsilon Z} x[n]\, \psi_{a,b}\, [n] \tag{4.1}$$

where a is the dilation or scale, b the translation, and $\psi_{a,b}$ represents the discrete wavelet which is expressed as

$$\psi_{a,b}\,(n) = \left(\frac{1}{\sqrt{a}}\right) * \psi(\frac{n-b}{a}) \tag{4.2}$$

For dyadic wavelet transform, $a=2^{-j}$, $b=k*2^{-j}$, $\psi_{a,b}\,(n) = 2^{j/2} * \psi[2^{j}_{n-k}]$ with $k\epsilon Z,\ j\epsilon N$. The DWT analyzes decomposing the signal into a coarse approximation and detail information. The original signal $x[n]$ being filtered via high pass filter $h[n]$ and a low pass $g[n]$ produces output of the first level decomposition, which can be respectively expressed as

$$y_{high}\,[k] = \sum_n (x\,[n] - h[2k-n]) \tag{4.3}$$

$$y_{low}\,[k] = \sum_n (x\,[n] - g[2k-n]) \tag{4.4}$$

It is to be mentioned that $y_{high}[k]$ and $y_{low}[k]$ are obtained after performing a down sampling by 2 operation. The above procedure can be repeated for further decomposition. A simplified block diagram explaining the above DWT operation at level 1 is depicted in Figure 4.3. after the low pass filtering and downsampled operation, one will obtain approximate coefficients (cA_1) and after the high pass filtering and downsampled operation, one will obtain detail coefficients (cD_1).

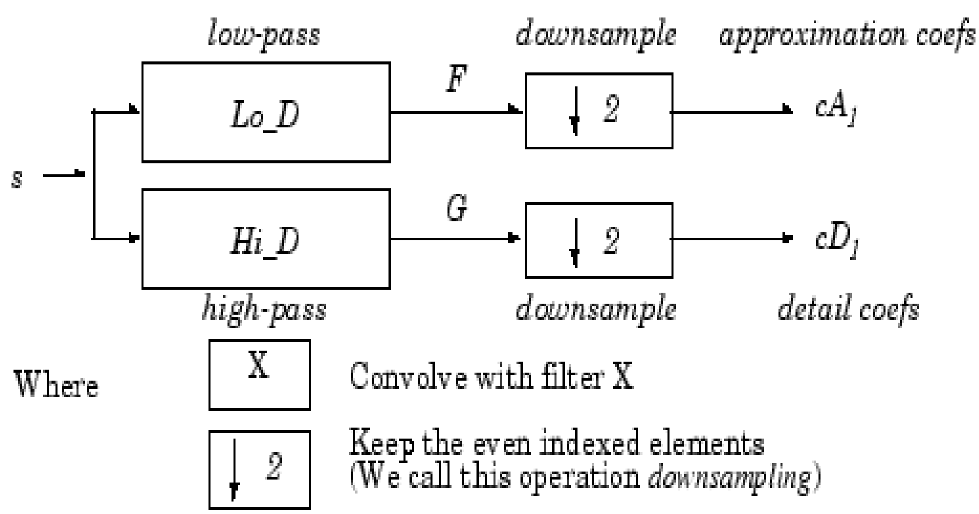

Figure 4.3: Block diagram representing the level-1 DWT on sEMG signal s[n]

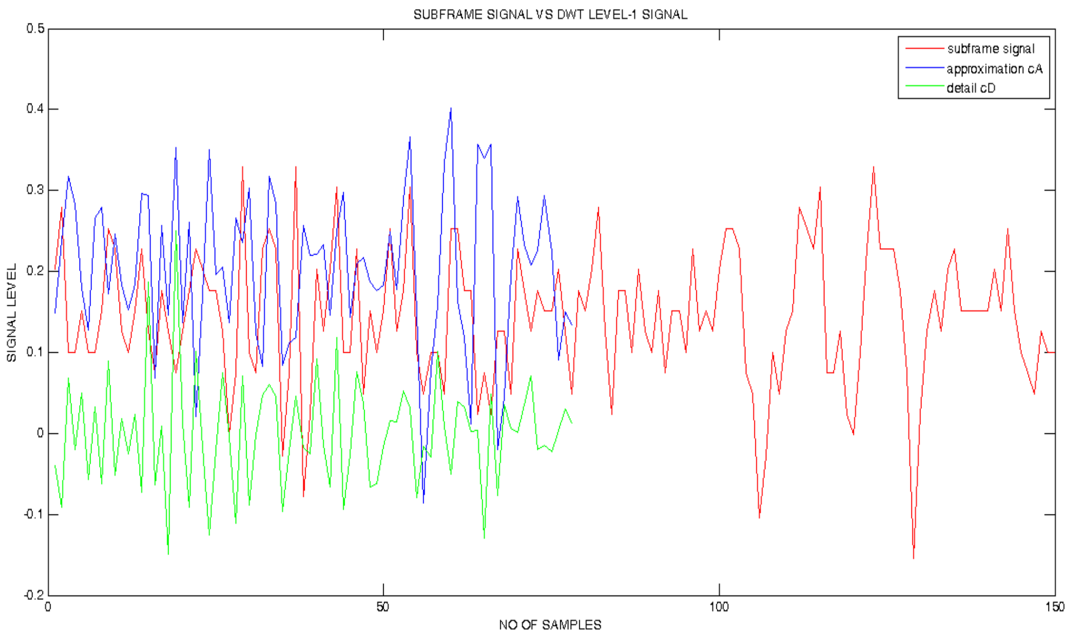

Figure 4.4: Sub-frame Signal versus DWT (cA and cD) Signal

Considering a sub-frame of sEMG data, the output of the level-1 DWT operation is shown in Figure 4.4. It is to be mentioned that, at every level of decomposition, the filtering and down-sampling will result in half the number of samples and half the frequency band spanned which is shown in Figure 4.4.

The efficiency of DWT decomposition is dependent on the appropriate selection of the mother wavelet function. Wavelet transform is mostly based on the mother wavelet function which identifies the correlated coefficients across multiple signals [24]. The classification and identification accuracy of the analyzing signal depends on the similarity between the mother wavelet function and the wavelet coefficients. The Daubechies (db) wavelet functions have been applied in several areas of research with the lower orders (db1 to db20) used most often [23]. There are some general guidelines to select the wavelets, such as Db4 is more suitable for signals that have linear approximation over the support of four samples. While Db6 is better suited for a signal approximated by a quadratic function over the support of six. Coiflet6 provides better data compression results while Db4 is more suitable for feature extraction [31]. For the feature extraction Db4 has been used here. According to Phinyomark et al. Daubechies wavelet function with 2nd orders (db2) provide marginally better performance with a suitable decomposition level four. Some showed that db7 at level two works better. We choose db4 at level 1.

After performing the DWT on each sub-frame of sEMG data, the resulting wavelet transformed data are used for AR analysis and extracting AR reflection coefficients in a similar way as presented in Section 2.3.2. From the extracted sub-frame based reflection coefficients, an averaging is carried out to get the final feature vector, which depends on the order of the AR model.

4.2.3 Classification

In the proposed method classification is done by the k-nearest neighborhood (kNN) classifier. The k nearest neighbor algorithm is a nonparametric method used in pattern recognition. For the purpose of classifying the hand movements, the value of K is set equal to 5. The classifier in question considers a distance function [11] that is computed between the feature set of the test data and 5 neighboring patterns in the training data set. In the proposed method, classification is done using just the reflection coefficients obtained by fitting the DWT coefficients extracted from the sEMG data. As mentioned before, here a twentieth order AR model is chosen. These coefficients are the only extracted features of the filtered EMG data and no additional statistical features need to be cascaded with these coefficients in order to perform the hand movement classification satisfactorily. Thus a lot of computational time can be saved. Here we have performed signal classification by adopting two different approaches. One approach constitutes the classification of the EMG signals into two different classes in the beginning and then sorting them into six classes afterwards, referred to as hierarchical classification (h.c.). The second approach constitutes the direct classification of the signals into six different classes, total classification (t.c.).We have seen that for our particular dataset, the first approach is more fruitful seeing as the six actions can be distinguished into two distinct categories with little to no error. This is because three of the actions (cylindrical, hook and spherical) are far more forceful than the other three (palmar, lateral and tip). So, going ahead with two class classification and then sorting the members of these two classes into six different classes later on results in better classifier performance which automatically implies higher classification accuracy (depicted in Table 4.1).

4.3 Simulation Results

The performance of the proposed method described above has been investigated by conducting simulation on the dataset described before for six class hand movement classification. After feature extraction, the mean value of the subframe features are fed into kNN classifier. The features have been classified first into two classes and then three classes (h.c). Classification into direct six classes (t.c) have also been performed, but it was seen from the accuracy that the former method provides comparatively better accuracy, as observed in the Table 4.1.

Table 4.1 COMPARISON OF CLASSIFICATION ACCURACY USING DISCRETE WAVELET TRANSFORM

Subject	**Percentage Accuracy (%)**		
	Proposed method h. c (Class 2 then class 3)	**Proposed method t. c (Direct Class 6)**	**[9]**
Female-1	93.556 (%)	87.667 (%)	85.24 (%)
Female-2	81.000 (%)	80.222 (%)	83.88 (%)
Female-3	98.000 (%)	96.778 (%)	84.82 (%)
Male-1	97.778 (%)	94.556 (%)	86.92 (%)
Male-2	97.444 (%)	95.667 (%)	92.38 (%)
Average accuracy	93.556 (%)	87.667 (%)	86.65 (%)

For better evaluation of our performance, the results have been compared to the results obtained using the method mentioned in [9]. In that study [9], they have used eight statistical features. Also they have used linear classifier whereas kNN classifier has been used in our case.

4.4 Conclusion

Basic hand action movements can be classified by different types of conventional methods which can sometimes be tedious and computationally difficult. In this thesis, a simplified method is presented which helps in smoothening of the sEMG signal, enhancing correct extraction of feature values and thus appropriate classification. The hand movements can easily be divided into two classes depending on the number of neural firing and motor unit engagement. This difference assists in the classification of various number of movements, especially the six types which can be classified into two types and each of these two types can further be classified. Hence, hierarchical kNN classification is proposed to obtain better performance. Instead of extracting the features directly from the preprocessed data, each sub-frame of sEMG data is decomposed by using the DWT and then both the approximate and detailed coefficients are used for extracting AR reflection coefficients. It is to be noted that these AR reflection coefficients are not similar to those obtained in last two methods described in the previous chapters. Finally the average of all the extracted AR reflection coefficients is used in classification. As observed from Table 4.1, the result obtained by the proposed method is better than that is reported in the ref [9]. Therefore, the novelty of the proposed method is that, it can extract improved quality of DWT based AR reflection coefficient features and due to shorter feature dimension the proposed method is comparatively faster.

Chapter 5

Conclusion

5.1 Contribution of the Thesis

Our proposed method gives us good results with the four simple steps as follows:

5.1.1 Sub-Framing

Instead of considering the whole duration of the test data, we have divided each trial of the raw EMG signal into sub frames. Dividing the long data-set into short sub-frames ensures a constant local mean, which is a major advantage in estimation of consistent reflection coefficients by assuring stationary of the data. Computation of reflection coefficients in each sub-frame reduce the effect of random fluctuation in the given test frame. Even if there is any inconsistency in a whole test frame, it will not have significant effect on the overall performance accuracy due to sub-framing. On the other hand, any short duration changes in the whole test frame will be reflected in the corresponding sub-frame based estimation.

5.1.2 No Use of AR Parameter, Rather AR Reflection Coefficients is Used: We have used reflection coefficients instead of AR parameter because reflection coefficients are advantageous to use for signal classification.

1. The absolute value of each reflection coefficient is less than 1 when the AR system is not unstable. Such limitation in value is not achievable in the case of AR parameters seeing as their values differ from one another significantly.

2. Reflection coefficients have much higher immunity to noise than AR parameters. So using reflection coefficients as features to perform signal classification is the prudent course of action.

3. For slight differences in values of coefficients, reflection coefficients have the ability to render localization of spectral errors.

4. In order to determine reflection coefficients we do not have to go for the computationally expensive matrix inversion approach. Rather, a simple set of recursive equations affords us the required coefficients.

5. The reflection coefficients are determined iteratively by utilizing autocorrelation values. So increasing the number of reflection coefficients provide us with simply one new coefficient; the rest of the coefficients will remain unchanged. On the contrary, increasing the AR model order by 1 will give us a completely new set of AR parameters.

6. Therefore, reflection coefficients have been used effectively to construct our feature vector for EMG signal classification.

5.1.3 Unlike the nEMG signal decomposition of the sEMG signal into motor unit action potentials (MUAPs) is extremely difficult and there is no guarantee to obtain consistent MUAPs. Two different decomposition techniques are investigated in this thesis.

1. **Singular Value Decomposition (SVD):** A frame of sEMG signal is divided into overlapping sub-frames to construct a matrix and then singular values and principal components are computed using the singular value decomposition (SVD) of that sub-frame matrix. These singular values and the mean of the first five principal components are proposed as features to be used by the K nearest neighbor (kNN) classifier to perform the classification.

2. **Discrete Wavelet Transform (DWT) :** In order to analyze the effect of time-frequency domain decomposition of the sEMG data on the extracted feature quality, the discrete wavelet transform (DWT) is chosen. Each sub-frame of sEMG data is decomposed by using the DWT and then both the approximate and detailed coefficients are then used for extracting AR reflection coefficients. For the purpose

of classification, the k-nearest neighborhood (k-NN) classifier is applied in a hierarchical approach.

5.1.4 In this thesis our experiment has been tested on real data which gives the result with more accuracy. The result shows the competitive performance where different method offers good result for different person.

5.2 Scope and Future Work

It is quite possible that using our proposed method we will be able to analyze and classify other types of EMG signals. For instance, our proposed method may be put into use for the classification of different types of neuromuscular diseases like muscle fatigue, Parkinson's disorder etc. We may also think about applying this method in the analysis and classification of other types of bioelectric signals.

But the study in question is limited to just six basic hand movements. It remains to be seen how well the proposed method holds up in the case of a greater number of hand actions. Further development of our proposed method can surely contribute in the sector of prosthetic arms development and even in the classification of various neuromuscular diseases.

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