Comparative Analysis of Classifier for EMG Signals

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Declaration

I certify that this research work titled "*Comparative Analysis of Classifier for EMG Signals"* is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources it has been properly acknowledged / referred.

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Language Correctness Certificate

This thesis has been read by an English expert and is free of typing, syntax, semantic, grammatical and spelling mistakes. Thesis is also according to the format given by the university.

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Copyright Statement

Dedicated to my parents and adored siblings whose tremendous support and cooperation led me to this wonderful accomplishment.

Abstract

Electromyographic signals have a considerable importance in robotic hand prosthesis and various biomedical applications. The analysis of these signals for pattern recognition of arm movements is helpful to facilitate the handicap individuals with upper limb impairment or paralyzed individuals who are able to reinstitute innate control of hand. The techniques based on this analysis are not natural and demands prolonged training duration but the application of these methods is emerging successfully. As the difference in the configuration of these signals depends on the different muscle activities, they need to be recorded from the patients hand with the help of electrodes which may be contaminated with noises or undesired signals which affect the output accuracy. To ensure the detection of data with reduced noise and to execute the optimal performance from the analysis, the signals are preprocessed. The data collected for the 52 movements from 27 different subjects is provided by NinaPro database which is viable in attaining effective hand prosthetics and allowing the whole research community to add more advancement to this field. The purpose of this thesis is to analyze the dataset from this easily accessible database for twelve finger and hand movements acquired from 27 subjects. These signals are then processed with frequency filtering and data windowing to make them convenient for further use. Features extraction module consisting of four different features was then computed for these signals which are crucial step in gaining more dexterous myoelectric control of hand prosthesis. This processed data was then tested for two different classifiers to examine their percent classification accuracy. Two classifiers selected for this purpose were Linear Discriminant Analysis classifier and Artificial Neural Network classifier. The data classified with Linear Discriminant Analysis gives the mean classification accuracy of 85.41% while Artificial Neural Network classifier shows 91.14%. These performance results revealed that Artificial Neural Network performs better in the classification and recognition of data for hand movements as compared to Linear Discriminant Analysis.

Key Words: *Linear Discriminant Analysis, accuracy, classification, performance, Artificial Neural Network*

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CHAPTER 1: INTRODUCTION

Measuring the electrical signals generated by muscle activity, which includes contractions, relaxation or rest, is known as electromyography (EMG). The electrical signals generated by brain are transmitted to the muscles. EMG is able to sense if these signals fail to be sent properly or muscle fails to function properly. This situation needs an external source to stimulate the muscles.

EMG uses electrodes to detect the electrical activity, which is needed to design a device that is used to help the disabled patients to perform daily life activities like other normal people. For this purpose, information data about the activity of patients' muscles to perform contractions need to be available in order to make sure that this technique will not be harmful to patients in any case. This research focuses on the analysis of EMG data only for hand and finger movements.

1.1 Overview

Signals that can be measured from human beings are called biosignals. These are electrical signals produced due to the difference in electrical potential between specific cells. Researchers are trying to use these signals for the welfare of mankind from past several years. Few of the important bio signals known until now are EEG, ECG and EMG. One of the most important among them is EMG, which draws great interest of the researchers because of the recent advance technology.

The current trend of the researchers is based on the expertise in biological devices, which can be made possible due to the fact of present advance technologies in many of the engineering fields like electrical, mechanical, electronics etc. Due to these advances in technology, researchers are trying to make such devices with help of which a disable person can live a comfortable life. Up to some extent, they are able to achieve their goals similar to intelligent robots which are used in surgeries can perform their task more accurately than a human being.

Contribution of EMG signal is great in different fields like in the field of medical sciences it is used to record electrical activity of brain, most often in the treatment of epilepsy, sleep disorders etc. Besides medical field EMG signals are also used in sport sciences and many more. This research area focuses on the pattern of EMG signals generated due to the flexion and extension of wrist. As the signals generated by the muscle are in raw form and are passed through different processes to extract exact information. Depending upon the applications, different techniques are used for extracting information from raw signals so that they may be handled in a more intelligent way.

Great work on EMG has been done in the past couple of years but still some questions about these signals are unanswered, although current research helped very much in determining the nature of these signals. The purpose of this thesis is to focus on the basic knowledge of EMG signals, its processing and relate it with the muscular activities performed in daily life.

Many different components are used in this research, which includes a sensor for signal detection on the muscle, analogue to digital converter used to convert that EMG signal into digital form, software that is used for processing that data and a computer for storing that data.

1.2 Background

Two new methods for the prostheses of patients with low-level hand disabilities have been introduced which include electrically powered and myoelectric control. The reliability of EMG signals must be ensured in such disabilities as hand and wrist movements may be affected by intrinsic muscles and these signals may fail to act as good control signals so optimal function of hand movements must be preserved [1, 2-4].

The ability of EMG signals to recognize and differentiate muscle activities depends on the patient's capability of repeatable limb movements [5]. Those EMG features are considered to be efficient that give correct and detailed information about muscle movements and are not easily affected by the factors such as electrode shift [6] etc. that pollute the EMG data and reduce its accuracy. Various features were found to be reliable against such unwanted factors but since researchers were interested in applications to more genuine disabilities so they, somehow, neglected the behavior of feature to hand movements. The workability of features is tested for all the channels and some researchers have found that selecting specific features from different channels perform in a more beneficial way. This may be useful only against the unwanted signal interruption of wrist muscles into those of other limb muscles, as intrinsic muscles are not affected by such disturbances.

Researchers have worked on different classifiers such as Artificial Neural Networks [7], Linear Discriminant Analysis (LDA) [8], Quadratic Discriminant Analysis [9], Support vector machines [10] etc. for both intact subjects and amputees and they evaluated that there was a small difference in the performance accuracy of different classifiers [9]. It is also essential to determine which classifier is more accurate in classifying different limb movements. Although both linear and nonlinear classifiers work significantly but LDA classifier is considered to be the frequently used one because of its better classification accuracy as well as more efficient computationally.

If classification is done to control low-level prostheses i.e. wrist and finger movements, then the performance of a controller corresponding with the hand movement must be observed. Some researchers have investigated the amplitude modulation of EMG signals with respect to joint angles of hand [11, 12]. Some performed mean frequency modulation for joint angle variations [13]. Variations in joint angles due to internal factors can affect EMG features. If any joint angle for a muscle is altered, it changes positions and geometry of muscles fibers and other muscle units thus affecting the position of electrodes suitable for detection [13].

The current research advancement in classification and recognition control of hand prostheses has increased the workability of electrically stimulated hand prostheses [14]. This pattern recognition helps the patients to fulfill grasping tasks more easily by using surface EMG signals generated to classify patient's goal [14, 15]. This method is medically used for patients with high-level amputations and is needed to be made available for patients with low-level disabilities. This research is focused on the myoelectric classification control of hand and finger movements, for which the general framework is presented in Figure 1.1.

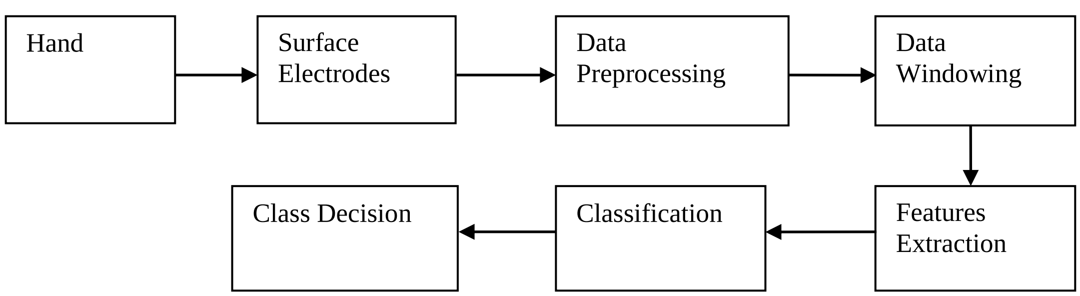


Figure 1-1: General framework of the stepwise methodology

1.3 Scope

The scope of my research is limited to the following main points given as under.

- As human body consist of hundreds of muscles but this thesis is focused on finger and wrist movements. Reason for selection of these muscles is that it has an easy excess and can be placed easily on it.
- As hand is very important part of human body, it is used in variety of functions an individual performs in everyday life.
- Different EMG signal detectors are present up to date like needles, thin wires etc. but my preference is to use a sensor which can be installed on the surface of skin to avoid any discomfort.
- Different techniques are used for the classification of EMG signals. Every approach has its own benefits. However, the techniques used in this research are Linear Discriminant Analysis (LDA) and Artificial Neural Networks (ANN).
- This research will be helpful to attain the workability of an automated physiotherapy monitoring system.

1.4 Motivation

Main aim of this research is to gain great knowledge about EMG signals and to make it available for particular use. Brain generates signals on the basis of which a muscle is contracted or relaxed. But the main problem is that as human body has large number of muscles so which nerve responds to which brain signal. So this research is based on the analysis of EMG signals as these signals are more helpful in determining the stated problem.

Efforts have been made for a long time to improve human's life. In the same way EMG signal analysis can bring great change in the life of disabled people. Experiments have shown that disabled people can generate detectable EMG signals by their own effort (Walker et al.1998). According to this hypothesis, brain can generate signals even for a lost body part. So this work got an insight to develop a classification system which helps to classify a pattern of EMG signals generated by a group of intact subjects performing a particular muscle activity. In this way, this study builds a concept to develop a system that is workable and convenient for amputees as well.

Generally, it is observed that patients with biceps injuries or damaged upper limb, having physiotherapy treatment, are given training in order to recover that accused muscle to the original position. However, all this process is done manually and a very few automatic rehabilitation software are present. Therefore, there is a need to develop a system to do this task automatically and in a more comfortable manner. Software developed in this field can also in return make good profit for the developer. This study is very helpful in developing such software.

1.5 Problem Statement

EMG signals are inherently very complex but on the other side, easy to use. Like other biological signals like ECG, EEG, EMG has very small amplitudes as well as are very much sensitive which creates a major problem in the acquisition stage. Due to these shortcomings, values of these signals are sometimes imperfect and doubtful.

Another major problem in the processing of EMG signals is to keep them free from unwanted signals and frequencies that can be added by different sources like power lines, radio signals, unnecessary filtering or any other source, which can distort main EMG signal. Because of these issues, detecting and recording must be done to process the signal in its pure form.

Besides these interferences, other factors like skin resistance, electrode quality, its location and other devices and cables used in the system greatly affect the accuracy of EMG signals. To avoid these problems, many considerations must be kept in mind in order to develop a system with good results.

In addition to this, EMG signals are difficult to classify in a sense that for a specific body movement, EMG signals generated by muscle activities may vary from person to person.

Even each subject may generate different EMG signals with different signal amplitudes for the same muscle movement. These problems make the analysis and classification of EMG signals very difficult.

1.6 Objectives

Main objectives of the research are given below.

a) To use the preprocessed EMG data recorded from the hand movements of intact subjects and amputees for features determination and improved classification.

b) To find and study different features of EMG signals as a differentiating factor for different movements performed by wrist and fingers.

c) To design a system which can analyze the EMG signals received to classify different finger movements using Artificial Neural Networks (ANN) and Linear Discriminant Analysis (LDA) classifier.

d) To compare the performance of ANN and LDA classifiers.

CHAPTER 2: LITERATURE REVIEW

As discussed earlier, surface EMG (sEMG) is used to measure the motor signals generated by brain by mounting electrodes on patient's limb surface. It has been verified that even the nervous system of a disabled person can generate perceptible EMG signals without any external aid [16]. Generally, EMG has information to assess the muscle movements and control [17]. These electrodes detect the arm activity of the subject from sEMG signals and then different pattern recognition techniques are applied for the classification of movement performed by the subject. The accuracy results for average classification recorded for 10 movements are below 80-90% [18], and may have maximum values up to 90% [19], [20]. This prosthesis is done to rehabilitate hands of disabled patients to perform functions normally. Researchers are trying to achieve this goal and working on this for decades. At early stages, they started with open close grasp control but now they are able to carry out many functions with hand prostheses. Although previous work has got remarkable results, more improvement needed to be added to this field. As studies were conducted for limited number of subjects i.e. 11 healthy and 6 amputated subjects [21] and small number of movements i.e. about 12, so the results obtained might be uncertain. For large number of movements considered, each of them must be recognized with highest accuracy to carry out the real life tasks as desired perfectly. No standard data base was publicly provided that's why results obtained from research work done separately couldn't be compared. So some studies highlighted the importance of publicly available standard data set and evaluation protocols [22], [23] which made it possible to compare different classification approaches. In spite of a lot of achievements and development in this field, the use of this technology is comparatively very low [24] as patients are unable to control these devices and these devices have low usability.

The use of static (steady-state) and dynamic (transient) phases of EMG signals simultaneously enable system's improvement [25], [26], [27]. Variations in posture cause unwanted effects which can be reduced by utilizing various static hand postures e.g. (five [28], five [29] and three [30]) for training. Similarly, processing the classifier for dynamic motions also facilitate EMG recognition control keeping in view the dependency of some hand movements upon the other body postures. Studies related to the use of combination of static (four hand movements) and dynamic motions (three hand postures) for seven different movements revealed that the classification rate is genuinely influenced by training the classifier in one posture and observing in the other [31]. The classification error was investigated to be minimized if information is collected from various hand conditions.

Thus most recent publicly available database named NinaPro (Non Invasive Adaptive Prosthetics) database is based on the data of 52 upper limb movements repeated many times for some time span collected from 27 intact subjects. It consists of EMG information of more number of subjects as compared to other datasets and also uses data obtained from healthy subjects to ensure more accuracy [32]. The machine developed for the prostheses purpose supports human-computer interaction which may be interfaced with other intelligent systems and robots used for rehabilitation purpose.

Researchers have investigated that in view of recent advancements in robotics, accessibility and usability of mechanically functional prostheses is not a problem nowadays. But its limited use and workability is just because of the less advanced myoelectric control as they have got robust hardware for prosthetic purposes. Researchers need to have a keen focus not only on extracting correct and reliable information from EMG signals but also improve the classification methods to achieve better control results. Although a lot of success has been achieved in this research work but it is still unclear that which technique is functionally more applicable and gives desired performance. These techniques are only workable for the trademarked dataset which consists of information about different hand movements taken from different subjects. It is still a challenge for the researchers to develop a robotic prosthetic hand which work perfect like a normal human hand.

Since considerable progress has been gained in the field of prostheses based on sEMG control, various approaches presented in this regard follow same procedure with common steps which include data acquisition, preprocessing, feature extraction and several artificial intelligence and signal processing techniques for classification. Initial stages of these approaches require suitable use of number and placement of electrodes which has a notable influence on final results. This research is restricted to the feature extraction and classification phases of sEMG analysis.

The precise features selected for the analysis of sEMG signals depends on the domain in which they are applied, such as features representing force applied at joints [33] or behavior of motor units [34]. The useful feasible methods of extraction use amplitude, zero crossing (ZC) and spectral properties of the observed signal and are considered to be applicable in the time domain e.g. Mean Absolute Value, Standard Deviation, Variance etc. or frequency domain e.g. Mean Frequency etc. Some advanced types of extraction methods are workable with both time and frequency domains but these are computationally inefficient although they contain more useful information [35, 36]. Englehart et al worked on the combination of time and frequency domain features and found that data obtained from the simultaneous use of the two domains is more useful in recognizing EMG patterns [8], [37].

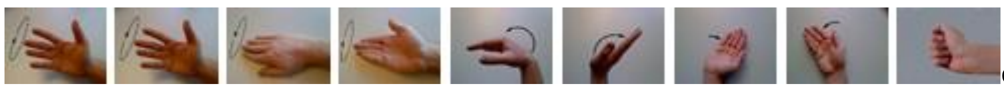
Several studies have been conducted to compare different extraction approaches and their performance was evaluated on the basis of final clustering and classification results [38], [39], [40], [41]. These studies showed different results by declaring different approach to be more precise. This conflict may be due to divergence in the acquisition protocols and hardware setups. Another reason for such unpredictable results is that previous studies didn't tested different classification techniques for extraction methods to explore the better one; instead a single classifier was used.

Investigators used several standard approaches for classification purpose, such as Linear Discriminant Analysis [38, 37, 8], Artificial Neural Networks, k-Nearest Neighbors [41] etc. and recently Support Vector Machine (SVM) [38], [20], [26] was explored. It was believed that feature representations have more impact on the final results of the analysis as compared to the classifiers, that's why investigating various types of classifiers was not encouraged. Hudgins et al, for the first time, inspected that data of EMG signals transients that lead to muscle contractions can be utilized for differentiating hand movements by using time domain features. He worked on ANN classifier to identify four distinct movements [7]. Hargrove et al. compared five different classifiers and observed almost same performance efficiency [42]. Lorrain et al. conducted comparison between SVM and LDA classifiers using autoregressive and time domain features and got equivalent results [26]. But other studies conducting comparisons revealed that various classification approaches give different performance results [43]. The reason for extracting variable results may be due to difference in the experimental setup as efficient non-linear classifiers may have improved performance as compared to linear classifiers with increase in the number of movements to be observed.

This work is focused on the comparison of classification techniques for 12 finger movements to figure out more robust classifier aiming to enhance the efficiency and workability of EMG prostheses system. The purpose of this research is to find a solution to this problem by comparing popular techniques of feature extraction and classification accuracy using the publicly available database NinaPro dataset [44], [45]. Apart from this, this thesis aims to find out which technique is comparatively more capable of acquiring desirable results.

(a) 12 basic flexions and extensions of the fingers

(b) 8 isometric and isotonic hand configurations


c

(c) 9 basic wrist movements

(d) 23 grasp and functional movements

Figure 2-1: The 52 movements considered in the NinaPro dataset [44].

CHAPTER 3: METHODOLOGY

EMG signal is a complex signal difficult to be analyzed because of the interruption of various types of noises as these signals move through body tissues. Similarly, sEMG signal is contaminated with unwanted noise signals while motor signals at the points of interest interfere with the signals extracted for analysis. Noise may also be caused due to the unstable amplitude of the EMG signals thus disturbing the analysis process. That is why these signals need to be processed and filtered to remove unwanted additions and make them reliable for further processing.

As previously discussed, analysis of EMG signals consists of several steps which includes preprocessing, feature extraction and classification. In this thesis, feature extraction and classification techniques have been selected on the basis of their importance in the current research work. Four features were selected for extraction and two classifiers for classification purpose.

3.1 Nina Pro Database

Muscle activity is monitored by using differential electrodes which gives a preprocessed and rectified form of raw sEMG signal. These electrodes use inbuilt frequency filtering techniques which are helpful to overcome high and low frequency transitions. Another combination of 12 electrodes consists of a base station which sample raw sEMG signal at 2kHz.

The Ninapro database cover 10 repetitions of 52 different hand movements obtained from 27 intact subjects. These 52 movements are divided into four main classes which include 1-12 finger motions, 8 hand positions, 9 Wrist angles and 23 grasping and activity movements.

These four classes are subdivided into three exercises (second and third classes are combined into second exercise)

1. Finger movements.
2. Isometric hand and wrist postures.
3. Grasping and activity positions.

This thesis is emphasized on the analysis of first exercise of movements while data is measured in the form of a successive series of 10 repetitions for each of the 12 movements. Each movement's duration is five seconds with a gap of three seconds of rest. First exercise is completed in 16 minutes, second takes 23 minutes and third lasts for 31 minutes. The dataset for each exercise is comprised of a matlab file having synchronized variables such as emg, glove, repetition, stimulus etc. for each subject [44].

During the experiment, subjects sit in front of a laptop with their hand on the desktop. Visual stimuli are received from laptop for each movement and data is recorded simultaneously from the measuring systems. The healthy subjects copy the movements in the movies displayed on the laptop screen using their right hand. The disabled patients try to follow the same movements using their damaged hand [46].

Using emg and repetition variables, data for 12 movements of each of the 27 subjects has been preprocessed. Features i.e. mean absolute value feature, zero crossing feature, slope sign change feature, waveform length feature, were extracted for the preprocessed data. The extracted data was then classified using neural networks and LDA classifier for 27 subjects.

3.2 Signal Processing

As EMG signal is a raw input which should be processed through various plants to obtain the desired results. The type and placement of electrode used for signals detection is selected keeping in view the thickness of epidermal layer of skin and type of the part of the muscle to be treated. Electrode made up of Silver –Silver Chloride is used in order to minimize the unwanted interruption of signals into the readings [47]. Noise can also be overcome by maintaining favorable environment during the experiment, by choosing suitable electrode positions and proper signal processing and circuit configuration [48][49].

The efficiency of sEMG signals can be maximized by fixing electrodes at the muscle’s belly away from tendons. In case of bipolar configuration of electrodes with three surfaces used for recording, distance between the two electrodes should not be more than 2cm [50]. These surfaces are attached with the differential amplifier.

EMG signals may be contaminated by various noise factors such as causative factors i.e. direct affect which may be extrinsic factors i.e. improper electrode separation and electrode position etc. and intrinsic factors i.e. environmental or anatomical etc. The noise factor caused by the environment must be reduced by increasing the signal to noise ratio (SNR) of the EMG signal to get more useful signal [51]. Similarly the proper installment of electrodes and circuitry may help to overcome the noise inducted by electromagnetic devices. If eliminating noise from EMG signals is ignored, desired results cannot be achieved.

After recording, all the data from the database are leveled up to the highest frequency i.e. 100 Hz and then low pass filtered at 1 Hz. In order to remove the garbage data stored during switching from rest to movement state, data of each movement is segmented into three equal parts and the information from the middle segment is collected. Then the data of the middle segment is further processed by taking its average and one sample for each movement repetition is selected. Thus ten samples are collected for each movement with ten repetitions. The data thus obtained for each subject is then normalized at zero mean for sEMG signals having unit standard deviation [44].

3.3 Features Extraction

Next step in the analysis of sEMG signals is features extraction. This technique is used to obtain appropriate set of features known as feature vector by collecting pertinent information and refusing extraneous data from the raw EMG data. To determine the accurate features representing desired output tasks, feature vector obtained should have all the useful and efficient information derived from the EMG signals. If these signals are subjected to classification methods without processing them carefully with features extraction, their output performance will not be satisfactory and will be inefficient computationally. So this step is of high significance using these features as input to the classifier to ensure better classification results but their properties such as computational cost, robustness, complexity etc. should never be ignored [39]. Studies revealed that the proficiency of analysis of EMG signals for pattern recognition is completely dependent upon the selection of features.

As described in the previous chapter, features extraction can be conducted in time domain, frequency domain and time-frequency domain. This thesis deals with the four time domain features extracted for EMG data.

Time domain features are more feasible to use as they are computationally efficient and less complex compared to frequency domain features. These features do not require complicated hardware system rather applicable by using even a microprocessor or a mobile phone while time-frequency domain features extraction approaches are used for advanced MCI systems and transient myoelectric classification with more information but have drawbacks of high dimension and resolution. Time-domain features are more helpful to be used for dimensionality reduction purpose thus are well suited for sEMG pattern recognition.

Time domain features introduced by Hudgins et al. include mean absolute value (MAV), zero crossing (ZC), slope sign change (SSC) and waveform length feature (WL) [7, 8, 52] thus are known as ‘Hudgins feature’. The four features extracted in this study are explained shortly as follows:

Mean Absolute Value (MAV)

The average computer calculated value of the absolute data of EMG signal is called mean absolute value. It is a well-known time domain feature for EMG controlled techniques and an easy method to identify the muscle contractions.

This value is similar as the average rectified value denoting the area under the EMG signal after its rectification thus converting all negative values of the voltage to positive. Same as the root mean square value (RMS), it represents the amplitude of the EMG signal but RMS is favored in most cases as unlike MAV, it gives the power value of the EMG signal.

Zero Crossing (ZC)

The point at which mathematical function alters its positive or negative sign in the graph of that function denoted by a zero value at the boundary of the axis is called zero crossing. In alternating current, voltage is zero at ZC. In EMG, this point shows how many times a signal passes through zero within an analysis window thus related to signal frequency. This feature uses a threshold value to minimize the number of low-level noise signals crossing through zero.

Slope Sign Change (SSC)

In case of EMG, slope sign change feature determines the number of times the sign of the slope of signal waveform within an analysis window is changed. This feature also uses a threshold value in order to reduce counts induced by noise.

Waveform Length (WL)

Waveform length feature illustrates a measure of signal complexity. It defines the progressive length of the signal within the window selected for analysis.

CHAPTER 4: CLASSIFICATION ANALYSIS AND RESULTS

The classification of EMG signals is vital for diagnosis of various diseases that needs to be simple, fast and reliable. The classification of movements is significant in the design of rehabilitation systems and robots and control of multifunctional prosthetic limb. Since there is a difference between the EMG signals taken from the healthy persons and from those with any kind of neurological disease or disability having movement disorders, thus several studies utilized these signals obtained from the muscle tissue for the diagnosis and identification of various diseases or neuromuscular fatigue. Similarly remarkable work has been done recently on developing efficient signal patterns for fatigue classification, relevant to the sports science. The high classification accuracy is very crucial as it makes the life of patients having limb disability much comfortable for which selection of quality features for extraction is of great significance [53]. Furthermore, effective dimensionality reduction techniques and suitable classifiers must be introduced in order to ensure flawless pattern recognition.

Recent research work has been focused keenly on the classification of patterns of EMG signals. Various types of classifiers were introduced which are applicable efficiently for several EMG purposes. Some of them are named as Artificial Neural Network (ANN), Linear Discriminant Analysis (LDA), Support Vector Machines (SVM) and fuzzy classifier [54]. As mentioned above, raw EMG signal is processed through feature extraction to obtain a feature vector which acts as an input to be classified for pattern recognition. This step enhances the information solidity of the signals used for pattern classification [9]. Due to the unpredictable nature of the raw EMG signals, they cannot be directly supplied to the classifier by overkilling it instead dimension reduction approaches are applied to minimize the features dimension. These methods lower the load and computational time on the classifier. Principal Component Analysis (PCA) and LDA are used for this purpose but need more computational time for which researchers are introducing various algorithms to maintain robustness and efficiency of the classification process. These methods are helpful in enhancing the classification accuracy of the EMG prosthesis [55]. However some researchers combined other techniques with PCA for this purpose to attain even better classification results. Recent studies are widely using LDA classifiers as they are simple and easy to be implemented and trained [9, 56].

LDA is a linear classifier which also acts as dimensionality reduction method. It is helpful in both binary and multi-class classification with definite output variable. Each input variable given to this model should have same variance and the data standardized with 0 mean and unit standard deviation. LDA predicts the probability that each class has new inputs set. The class with high probability is predicted to be the output class. This model evaluates the mean and variance of data for every class. A new feature space for the data is introduced in order to increase the separation among the classes. In this case, the spread of data is not considered so the distance between the means calculated for each class may not be the only perfect one. To solve this problem, Ronald Fisher suggested the increase in function that denotes the separation between the means of each class and decrease in spread within each class. This assumption is only valid for the data set with Normal distribution.

Researchers have emphasized the use of neural network classifier for EMG analysis as it can deal with both linear and nonlinear properties of the data collected for analysis. ANNs resemble the formation of biological neural networks and are nonlinear unsupervised learning mechanism capable of modeling and processing EMG data statistically. Del and Park proposed the ANN as the preferable tool to represent the real-time implementation of EMG which can identify the myoelectric signals more precisely [57]. The output obtained from this technique denotes the extent to which immobilized muscle stimulation is insisted over a synergy [58]. Studies have shown that ANN has been used for the classification of six upper limb movements. Recent research work has enhanced the use of this approach for classification purpose with more improved performance.

The inputs to the ANN may be an image or pattern in vector form denoted by x(n) while n represents the number of inputs. Neural networks choose the weights based on the information of the problem which shows the quality of the interconnection between neurons within the neural system and each weight is multiplied to each corresponding input. All the resulting inputs are then summed up within figuring unit. If the sum is zero, the system output is valued up by adding bias which always has unit input and unit weight. So the output value may range from 0 to infinity. To obtain a desired sum value, a transfer function in the form of activation function is applied to the sum by setting up a threshold value.

The NinaPro database 1 is comprised of EMG data detected for 12 finger movements acquired from 27 subjects. The data for four of the subjects is demonstrated below.

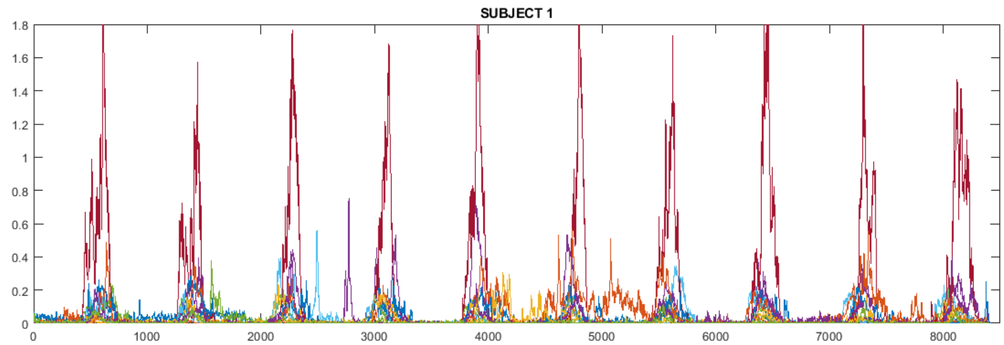


Figure 4-1: EMG data obtained for 12 finger movements from Subject 1

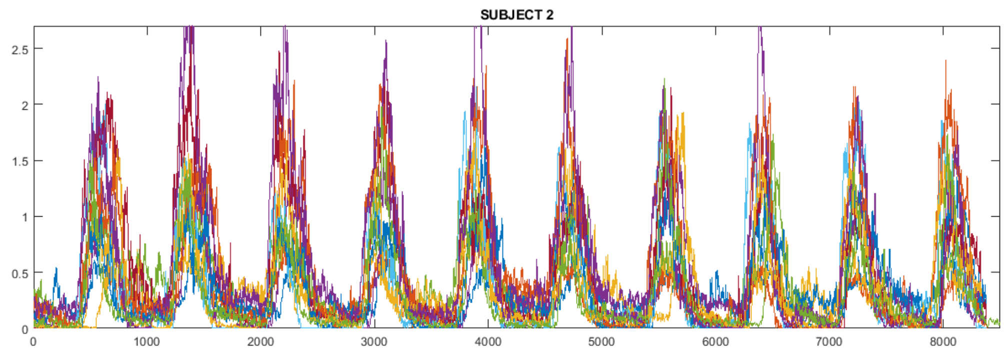


Figure 4-2: EMG data obtained for 12 finger movements from Subject 2

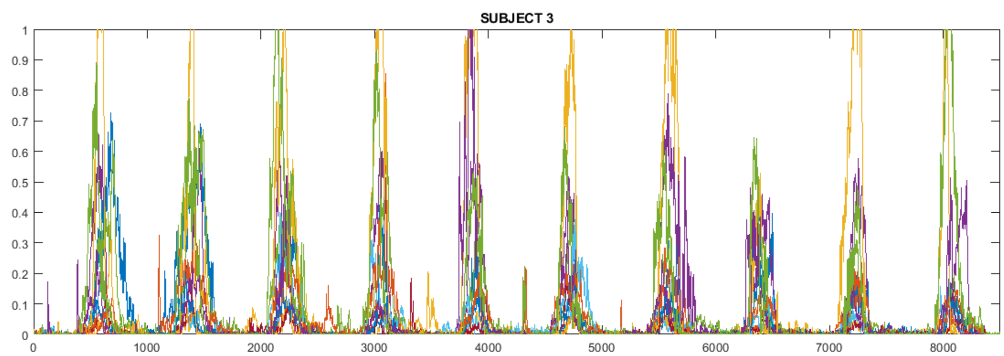


Figure 4-3: EMG data obtained for 12 finger movements from Subject 3

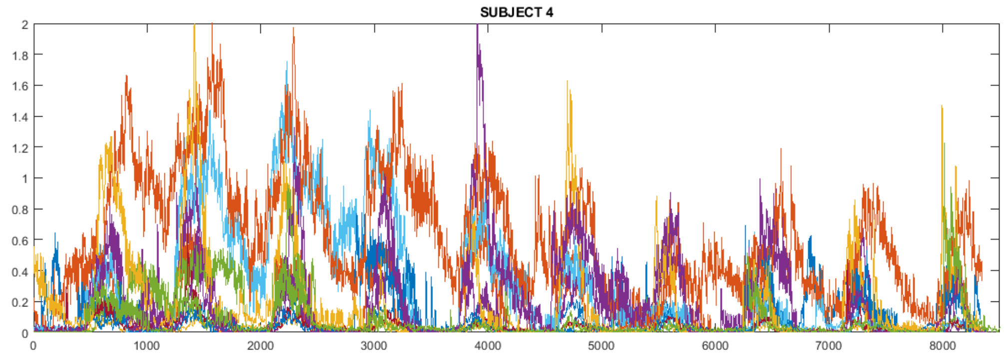
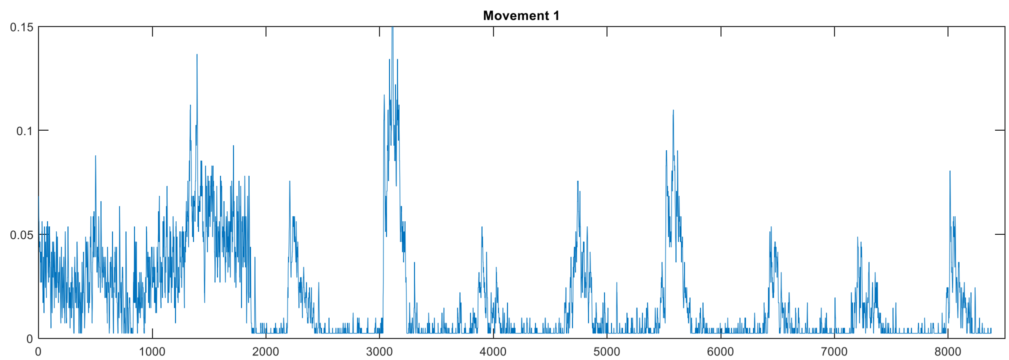
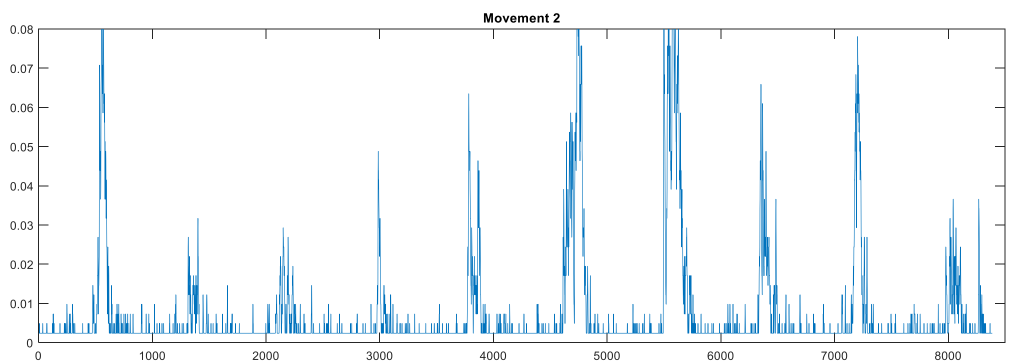


Figure 4-4: EMG data obtained for 12 finger movements from Subject 4

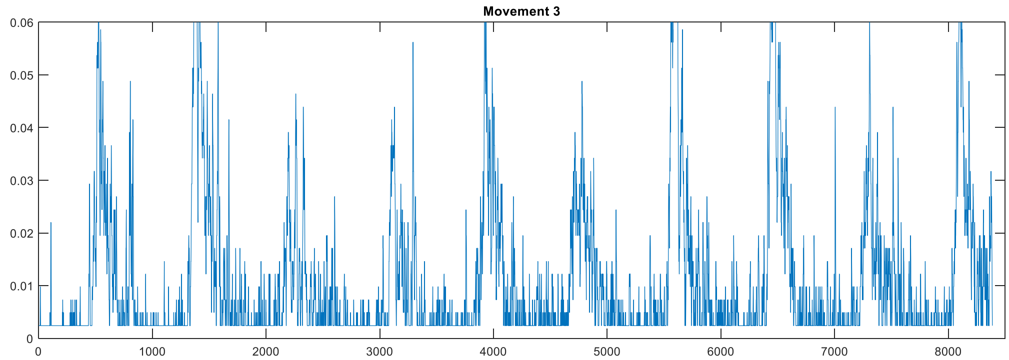
Twelve movements for subject 1 each having ten repetitions with small intervals of rest are represented as follows.



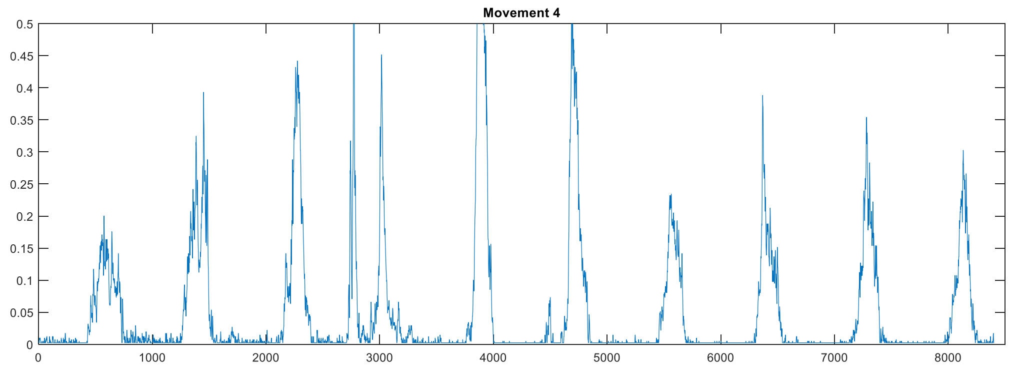
(a) Figure Movement 1



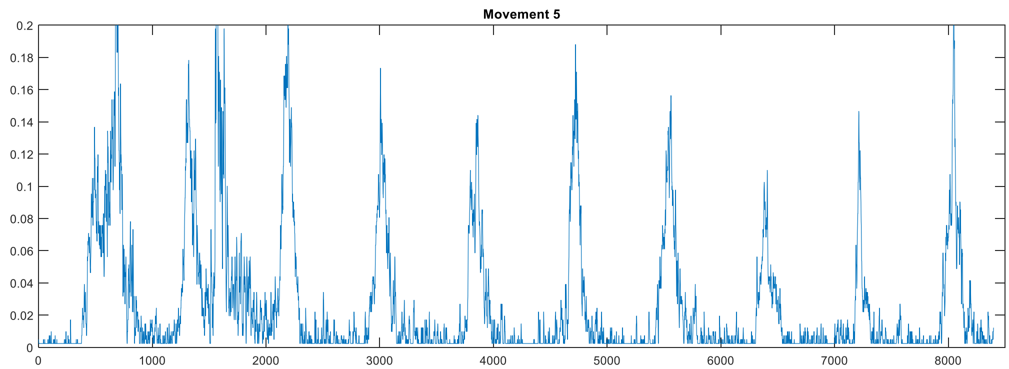
(b) Figure Movement 2



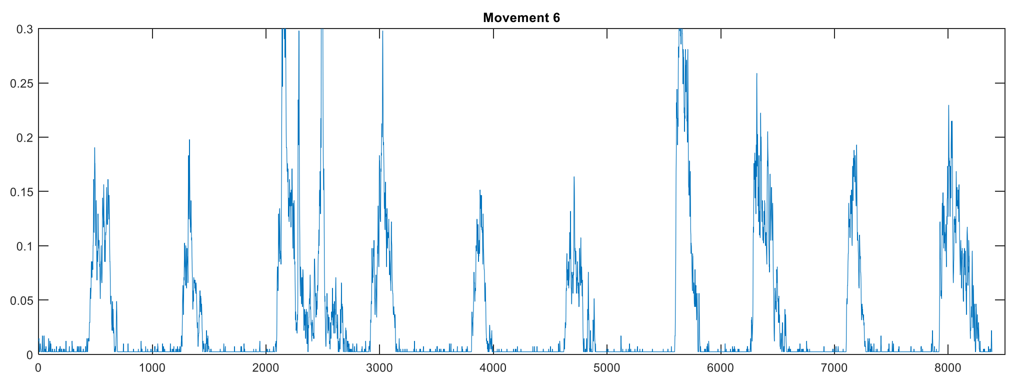
(c) Figure Movement 3



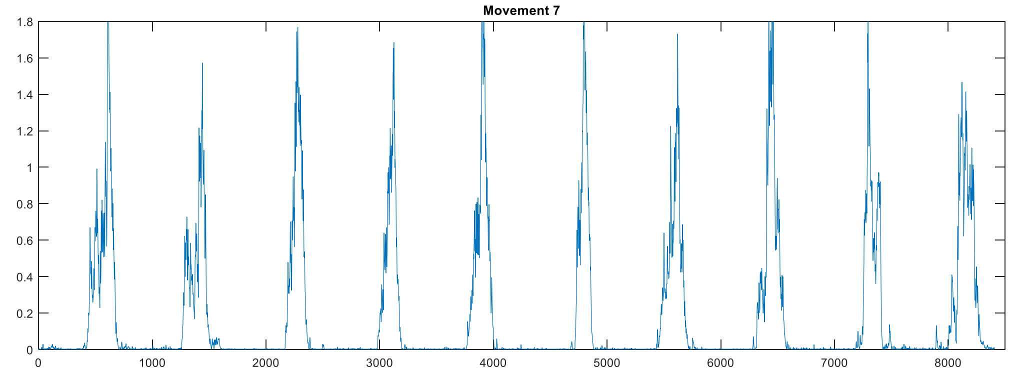
(d) Figure Movement 4



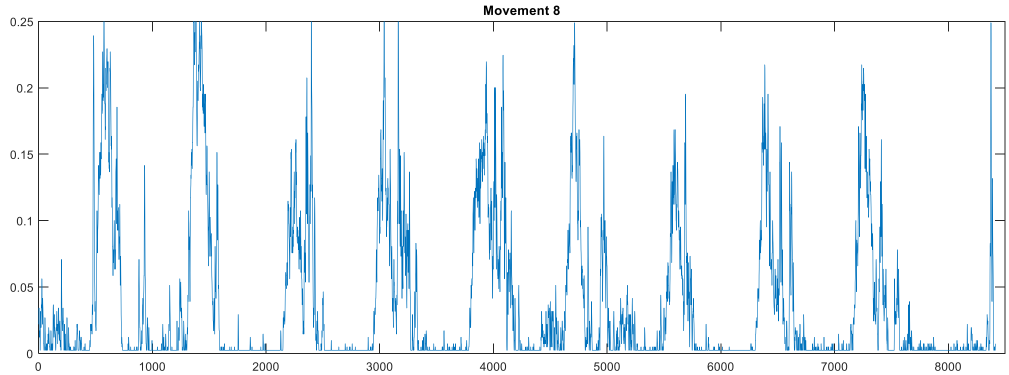
(e) Figure Movement 5



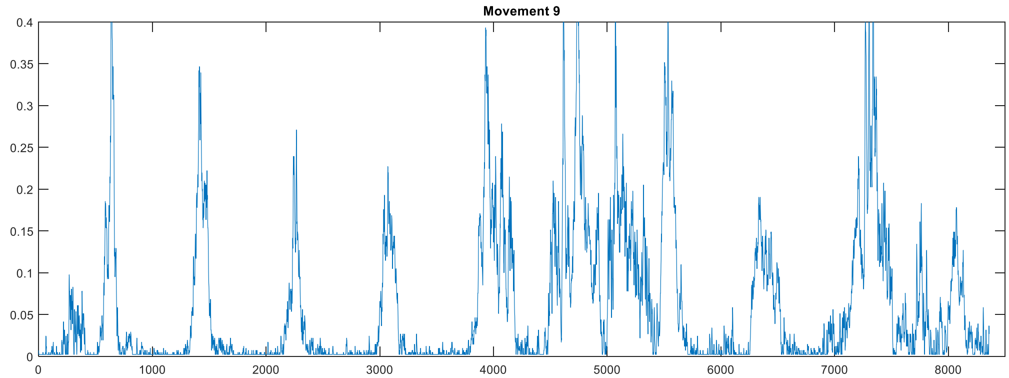
(f) Figure Movement 6



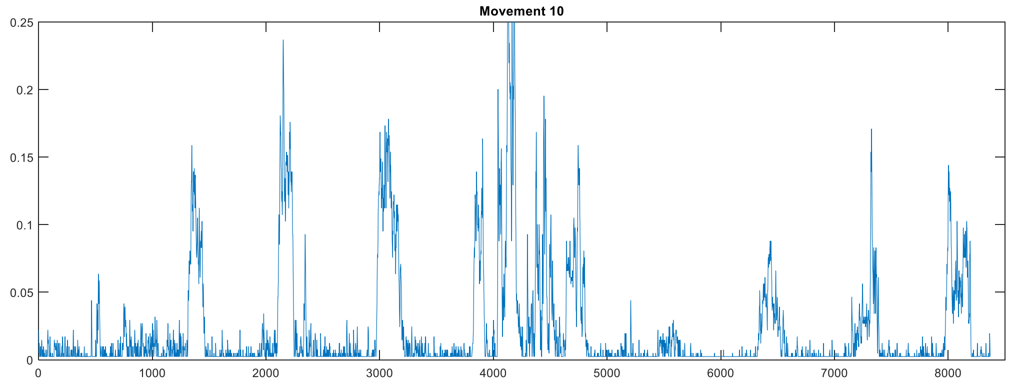
(g) Figure Movement 7



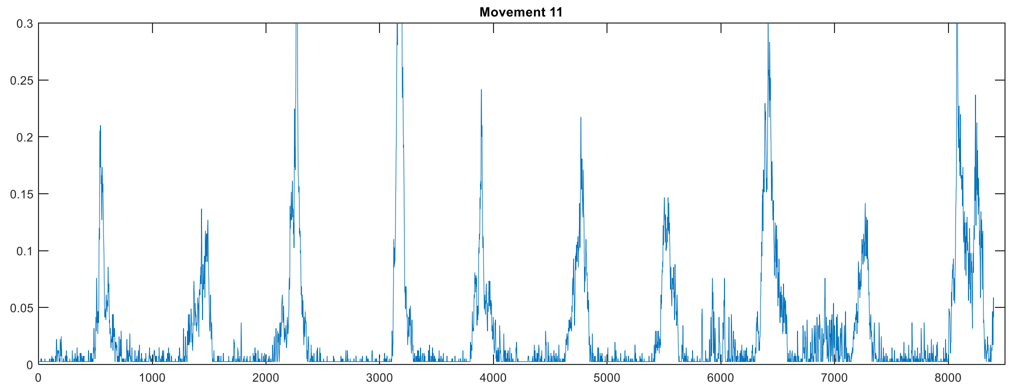
(h) Figure Movement 8



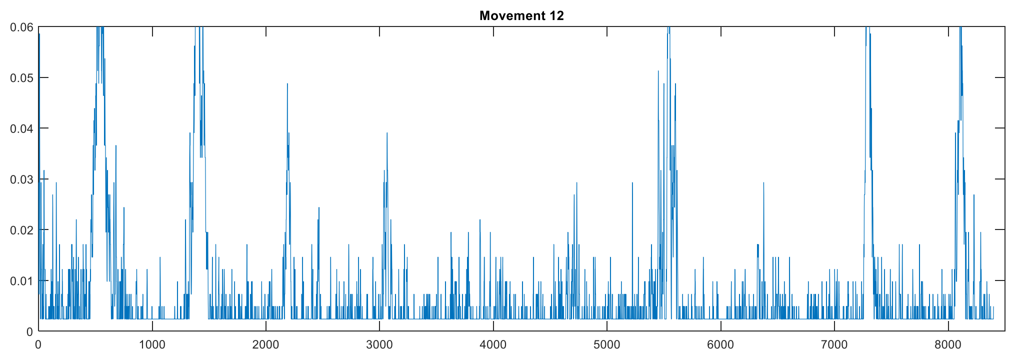
(i) Figure Movement 9



(j) Figure Movement 10



(k) Figure Movement 11



(l) Figure Movement 12

Figure 4-5: Twelve movements for subject 1 (each with ten repetitions)

In this thesis, the two classifiers LDA and ANN were used for classification of features extracted from the EMG signals. The performance accuracy of the two classifiers was compared.

Table 4-1: Performance Accuracies of the classifiers

	SUBJECTS	ACCURACIES OF ANN classifier (Percentage %)	ACCURACIES OF LDA classifier (Percentage %)
1	Subject 1	89.31	81.67
2	Subject 2	94.22	79.01
3	Subject 3	92.10	83.11
4	Subject 4	94.03	85.24
5	Subject 5	95.01	90.32
6	Subject 6	87.43	86.01
7	Subject 7	90.67	81.21
8	Subject 8	93.89	84.76
9	Subject 9	88.47	87.44
10	Subject 10	92.42	91.09
11	Subject 11	91.05	82.72
12	Subject 12	90.11	89.34
13	Subject 13	87.83	87.67
14	Subject 14	94.06	89.89
15	Subject 15	88.35	84.37
16	Subject 16	90.48	83.40
17	Subject 17	93.58	87.05
18	Subject 18	91.69	88.92
19	Subject 19	85.33	81.67
20	Subject 20	92.09	89.98
21	Subject 21	87.49	84.00
22	Subject 22	94.43	86.85
23	Subject 23	91.74	82.34
24	Subject 24	95.01	83.52
25	Subject 25	94.67	86.31
26	Subject 26	86.46	84.76
27	Subject 27	88.92	83.45
Average Accuracy (%)		91.14	85.41
Mean Accuracy $\pm$ Standard Deviation		91.14 ± 2.88	85.41 ± 3.19

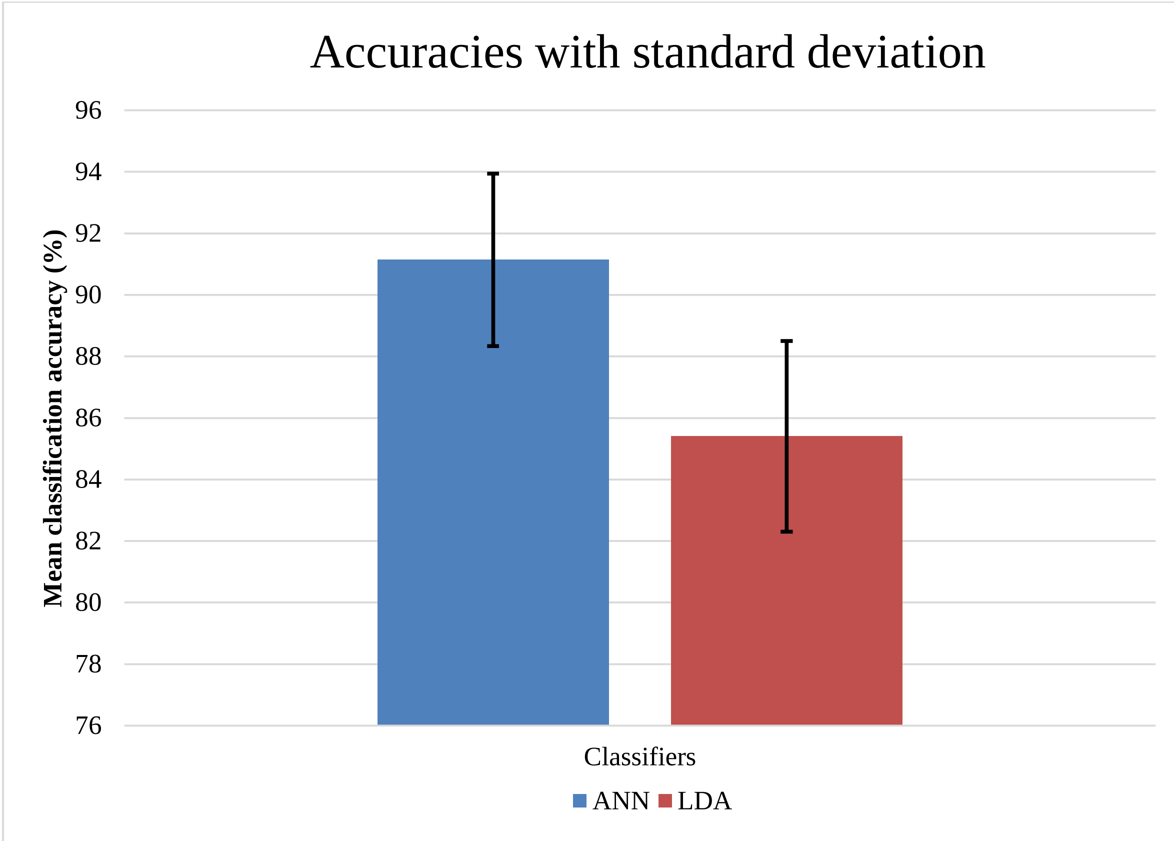


Figure 4-6: Visual Demonstration of Accuracies with standard deviation, for the classifiers

The results of this study show that the performance of Artificial Neural Networks classifier for the classification of twelve finger movements is way better than the results obtained for LDA classifier as the mean percent classification accuracy attained by ANN classifier is 91.14 while that achieved by LDA is 85.41 which is poor compared to that of ANN classifier.

Friedman test

The Friedman test is the non-parametric alternative to the one-way ANOVA with repeated measures. It is used to test for differences between groups when the dependent variable being measured is ordinal. When you choose to analyze your data using a Friedman test, part of the process involves checking to make sure that the data you want to analyze can actually be analyzed using a Friedman test [59].

The p-value is a probability that measures the evidence against the null hypothesis. Lower probabilities provide stronger evidence against the null hypothesis. Use the p-value to determine whether any of the differences between the medians are statistically significant. To conclude this, compare the p-value to your significance level to assess the null hypothesis. The null hypothesis states that the population medians are all equal. Usually, a significance level (denoted as α or alpha) of 0.05 works well. A significance level of 0.05 indicates a 5% risk of concluding that a difference exists when there is no actual difference [60].

This test is performed to check whether ANN is really a better classifier. If p-value is less than 0.05, it means ANN is better classifier and if it is equal to or less than 0.05, both classifiers will have same accuracy.

Table 4-2:- Value calculation for classifiers

Statistical Friedmann test for P-value calculation			
Total Subjects	Mean accuracy with standard deviation		P value
	ANN	LDA	
27	91.14 ± 2.82	85.41 ± 3.12	1.2132e-07

P value was less than 0.05. Hence, ANN significantly outperformed LDA. However computational time of ANN (40 sec) was greater than LDA (0.5 sec).

CHAPTER 5: CONCLUSIONS AND FUTURE WORK

The aim of this study is to conclude a precise view of techniques used for processing EMG and to suggest more improvements on the pattern recognition approaches. The comparison will assist researchers to predict the better classifier for the analysis of sEMG signals and the work based on this study will be more helpful in clinical, arm prosthetic and biomedical fields.

This work deals with the analysis of the raw EMG data acquired from the NinaPro database for the identification of twelve finger and hand movements. This publicly available dataset contains data obtained from signals collected with the help of electrodes from the muscle activity of upper limb for ten repetitions of 52 different movements from 27 subjects. Out of 52 movements, twelve finger and hand movements for each subject were selected to be identified for this study. Two classifiers, ANN and LDA were evaluated and compared for the overall percent classification accuracy to identify these movements for four well-known features. The results of this thesis concluded that non-linear ANN classifier revealed better performance results as compared to linear LDA classifier.

The database used in this study is no doubt very helpful for providing easily available sEMG data, which is applicable efficiently for the recognition and classification of upper limb movements but still there are many challenges faced by bio robotics community and machine learning research in myoelectric control and recognition. This database maybe upgraded by increasing the number of both healthy and disabled subjects and adding data for dynamic variety of hand movements. This will further boost the functionality and versatility of the database to achieve more-reliable results. In order to meet the challenges confronted in this field, features that are more robust are to be selected and novel features extraction approaches have to be proposed. By increasing the EMG channels count and the number of features as input to the classifier, the count of control commands of the classification technique is also increased. This will help to acquire the remarkable classification outputs by providing more advanced and significant information from EMG. If large number of features is desired to be extracted, LDA should be preferred because of its dimensionality reduction property as data is converted to a space vector having low dimensions without wasting useful information. Furthermore, the recognition and control of movements maybe enhanced by comparing the classification ability of a variety of linear and non-linear classifiers and the mean accuracy achieved in this study may be further improved.

REFERENCES

[1] C. Lake, "Partial Hand Amputation: Prosthetic Management," in Atlas of Amputations and Limb Deficiencies: Surgical, Prosthetic, and Rehabilitation Principles, D. G. Smith, J. W. Michael, and J. H. Bowker, Eds., 3 ed Rosemont, IL: American Academy of Orthopaedic Surgeons, 2004, pp. 209-217

[2] M. Lang, "Challenges and Solutions in Control Systems for Electrically Powered Articulating Digits," in MyoElectric Controls/Powered Prosthetics Symposium, Frederickton, New Brunswick, Canada, 2011.

[3] F. Montagnani, M. Controzzi, and C. Cipriani, "Is it Finger or Wrist Dexterity That is Missing in Current Hand Prostheses?," IEEE Trans Neural Syst Rehabil Eng, vol. 23, pp. 600-9, Jul 2015.

[4] B. D. Adams, N. M. Grosland, D. M. Murphy, and M. McCullough, "Impact of impaired wrist motion on hand and upper-extremity performance(1)," J Hand Surg Am, vol. 28, pp. 898-903, Nov 2003.

[5] M. A. Oskoei and H. S. Hu, "Myoelectric control systems-A survey," Biomedical Signal Processing and Control, vol. 2, pp. 275-294, Oct 2007.

[6] A. J. Young, L. J. Hargrove, and T. A. Kuiken, "Improving myoelectric pattern recognition robustness to electrode shift by changing interelectrode distance and electrode configuration," IEEE Transactions on Biomedical Engineering, vol. 59, pp. 645-52, Mar 2012.

[7] B. Hudgins, P. Parker, and R. N. Scott, "A new strategy for multifunction myoelectric control," IEEE Trans Biomed Eng, vol. 40, pp. 82-94, Jan 1993.

[8] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," IEEE Transactions on Biomedical Engineering, vol. 50, pp. 848-54, Jul 2003.

[9] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: state of the art and challenges for clinical use," J Rehabil Res Dev, vol. 48, pp. 643-59, 2011.

[10] A. H. Al-Timemy, G. Bugmann, J. Escudero, and N. Outram, "Classification of Finger Movements for the Dexterous Hand Prosthesis Control With Surface Electromyography," IEEE Journal of Biomedical and Health Informatics, vol. 17, pp. 608-618, May 2013.

[11] J. A. Johnston, L. R. Bobich, and M. Santello, "Coordination of intrinsic and extrinsic hand muscle activity as a function of wrist joint angle during two-digit grasping," Neurosci Lett, vol. 474, pp. 104-8, Apr 26 2010.

[12] H. Onishi, R. Yagi, M. Oyama, K. Akasaka, K. Ihashi, and Y. Handa, "EMG-angle relationship of the hamstring muscles during maximum knee flexion," Journal of Electromyography and Kinesiology, vol. 12, pp. 399-406, Oct 2002.

[13] D. T. MacIsaac, P. A. Parker, R. N. Scott, K. B. Englehart, and C. Duffley, "Influences of dynamic factors on myoelectric parameters," IEEE Eng Med Biol Mag, vol. 20, pp. 82-9, Nov-Dec 2001.

[14] J. Uellendahl, J. Tyler, and K. Hung, "A Case Series Study of Pattern Recognition for Upper-Limb Prosthesis Control," in American Academy of Orthotists and Prosthetists 42nd Academy Annual Meeting and Scientific Symposium, Orlando, Florida, 2016.

[15] T. A. Kuiken, G. Li, B. A. Lock, R. D. Lipschutz, L. A. Miller, K. A. Stubblefield, et al., "Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms," JAMA, vol. 301, pp. 619-28, Feb 11 2009.

[16] J. B. Walker, B. Scroggins, M. Morse, Are paralyzed people really paralyzed ? Probably not according to EMG analysis, IEEE International Conference on Engineering in Medicine and Biology Society, pp 1137, 1998.

[17] L. S. Gary, M. K. Loretta, A guide for use and interpretation of kinesiology electromyography data, Physical Therapy, 80(5), pp 485-497, 2000

[18] B. Peerdeman, D. Boere, H. Witteveen, R. Huis in `t Veld, H. Hermens, S. Stramigioli, H. Rietman, P. Veltink, and S. Misra, "Myoelectric forearm prostheses: state of the art from a user-centered perspective," J. Rehabil. Res. Dev., vol. 48, no. 6, pp. 719–738, 2011.

[19] C. Cipriani, C. Antfolk, M. Controzzi, G. Lundborg, B. Rosen, M. C. Carrozza, and F. Sebelius, "Online myoelectric control of a dexterous hand prosthesis by transradial amputees," IEEE Trans. Neural Syst. Rehabil. Eng., vol. 19, no. 3, pp. 260–270, 2011.

[20] C. Castellini, E. Gruppioni, A. Davalli, and G. Sandini, “Fine detection of grasp force and posture by amputees via surface electromyography.,” J. Physiol. Paris, vol. 103, no. 3–5, pp. 255–62, 2009.

[21] F. C. P. Sebelius, B. N. Rosen, and G. N. Lundborg, “Refined myoelectric control in below-elbow amputees using artificial neural networks and a data glove,” J. Hand Surg. Am., vol. 30, no. 4, pp. 780–789, 2005.

[22] H. Müller, J. Kalpathy-Cramer, I. Eggel, S. Bedrick, R. Said, B. Bakke, C. E. J. Kahn, and W. Hersh, “Overview of the CLEF 2009 medical image retrieval track,” in Working Notes of CLEF 2009, Corfu, Greece, 2009.

[23] M. Everingham, L. Van Gool, C. K. I. Williams, J. Winn, and A. Zisserman, “The pascal visual object classes (VOC) challenge,” Int. J. Comput. Vis., vol. 88, no. 2, pp. 303–338, 2010.

[24] D. J. Atkins, “Epidemiologic overview of individuals with upper-limb loss and their reported research priorities,” Journal of Prosthetics & Orthotics, vol. 8, no. 1, pp. 2–11, 1996.

[25] D. Yang, J. Zhao, L. Jiang, and H. Liu, “Dynamic hand motion recognition based on transient and steady-state EMG signals,” Int. J. Humanoid Robot., vol. 9, pp. 11250007-1–11250007-18, 2012.

[26] T. Lorrain, N. Jiang, and D. Farina, “Influence of the training set on the accuracy of surface EMG classification in dynamic contractions for the control of multifunction prostheses,” J. Neuroeng. Rehabil., vol. 8, p. 25, 2011.

[27] E. Scheme and K. Englehart, “Training strategies for mitigating the ef- fect of proportional control on classification in pattern recognition based myoelectric control,” J. Prosthetics Orthotics, vol. 25, pp. 76–83, Apr. 1, 2013.

[28] A. Fougner, E. Scheme, A. D. Chan, K. Englehart, and O. Stavdahl, “Resolving the limb position effect in myoelectric pattern recognition,” IEEE Trans. Neural Syst. Rehabil. Eng., vol. 19, no. 6, pp. 644–651, Dec. 2011.

[29] Y. J. Geng, P. Zhou, and G. L. Li, “Toward attenuating the impact of arm positions on electromyography pattern-recognition based motion classifi- cation in transradial amputees,” J. Neuroeng. Rehabil., vol. 9, p. 74, Oct. 5, 2012.

[30] N. Jiang, S. Muceli, B. Graimann, and D. Farina, “Effect of arm position on the prediction of kinematics from EMG in amputees,” Med. Biol. Eng. Comput., vol. 51, pp. 143–151, Feb. 2013.

[31] J. Liu, D. Zhang, X. Sheng, and X. Zhu, “Quantification and solutions of arm movements effect on sEMG pattern recognition,” Biomed. Signal Process. Control, vol. 13, pp. 189–197, 2014.

[32] M. Atzori, A. Gijsberts, H. Müller, and B. Caputo, “Classification of hand movements in amputated subjects by sEMG and accelerometers.,” in Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2014, p. 63.

[33] C. De Luca, “The use of surface electromyography in biomechanics,”
Journal of applied biomechanics, vol. 13, pp. 135–163, 1997.

[34] R. Merletti and P. Parker, Electromyography: Physiology, engineering, and noninvasive applications. Wiley-IEEE Press, 2004, vol. 11.

[35] S. Micera, J. Carpaneto, and S. Raspopovic, “Control of hand prostheses using peripheral information,” IEEE Reviews in Biomedical Engineering, vol. 3, pp. 48–68, 2010.

[36] M. Zecca, S. Micera, M. Carrozza, P. Dario et al., “Control of multifunctional prosthetic hands by processing the electromyographic signal,” Critical Reviews in Biomedical Engineering, vol. 30, no. 4-6, p. 459, 2002.

[37] K. Englehart, B. Hudgins, and P. A. Parker, ‘‘A wavelet-based continuous classification scheme for multifunction myoelectric control,’’ IEEE Trans.Biomed. Eng., vol. 48, no. 3, pp. 302--311, 2001.

[38]M. Oskoei and H. Hu, “Support vector machine-based classification scheme for myoelectric control applied to upper limb,” IEEE Trans- actions on Biomedical Engineering, vol. 55, no. 8, pp. 1956–1965, 2008.

[39] M. Zardoshti-Kermani, B. Wheeler, K. Badie, and R. Hashemi, “EMG feature evaluation for movement control of upper extremity prosthe- ses,” IEEE Transactions on Rehabilitation Engineering, vol. 3, no. 4, pp. 324–333, 1995.

[40]F. Tenore, A. Ramos, A. Fahmy, S. Acharya, R. Etienne-Cummings, and N. Thakor, “Decoding of individuated finger movements using surface electromyography,” IEEE Transactions on Biomedical Engi- neering, vol. 56, no. 5, pp. 1427–1434, 2009.

[41] L. J. Hargrove, K. Englehart, and B. Hudgins, “A comparison of surface and intramuscular myoelectric signal classification,” IEEE Transactions on Biomedical Engineering, vol. 54, pp. 847–853, 2007.

[42]P. C. Doerschuk, D. E. Gustafon, and A. S. Willsky, “Upper extremity limb function discrimination using emg signal analysis,” IEEE Trans- actions on Biomedical Engineering, vol. 30, no. 1, pp. 18–29, 1983.

[43]K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, “Classification of the myoelectric signal using time-frequency based representa- tions,” Medical Engineering & Physics, vol. 21, no. 6-7, pp. 431–438, 1999.

[44] M. Atzori, A. Gijsberts, S. Heynen, A.-G. M. Hager, O. Deriaz,P. van der Smagt, C. Castellini, B. Caputo, and H. Mu¨ller, “Building the Ninapro database: A resource for the biorobotics community (submitted),” in Proceedings of IEEE International Conference on Biomedical Robotics and Biomechatronics (BioRob 2012), 2012.

[45]M. Atzori and H. M u¨ller, “NINAPRO project first milestone: Set up of the data base,” Institute of Business Information Systems, Univer- sity of Applied Sciences Western Switzerland, Sierre, Switzerland, Tech. Rep., 2012, available at http://publications.hevs.ch/index.php/ publications/show/1165.

[46] The Ninapro Database: a Resource for sEMG Naturally Controlled Robotic Hand Prosthetics

[48] B. B, "Adult Hemiplegia: Evaluation and treatment.," Oxford, Butterworth-Heinemann., 1990.

[49] S. D. C. G. C. Louise Ada, "Strengthening interventions increase strength and improve activity after stroke: a systematic review," Australian Journal ofPhysiotherapy, vol. 52, pp. 241-248, 2006.

[50] M. Z. Jamal, "Signal Acquisition Using Surface EMG and Circuit DesignConsiderations for Robotic Prosthesis," in Computational Intelligence in Electromyography Analysis –A Perspective on Current Applications and Future Challenges, InTech, 2012, pp. 427-448

[51] M. B. I. Reaz, "Techniques of EMG signal analysis: detection, processing, classification and applications," Cyberjaya, Selangor, www.biologicalprocedures.com, 2006, pp. 11-35.

[47] M.H.Jali, ‘I.M. Ibrahim, M.F.Sulaima, W.M Bukhari, T.A.Izzuddin and M.N.M. Nasir, “Features Extraction of EMG Signal using Time Domain Analysis for ArmRehabilitation

Device", International Conference on Mathematics on Mathematics,Engineering and Industrial Applications (ICoMEIA), 2014.

[52] Englehart, K.; Hugdins, B.; Parker, P. Multifunction Control of Prostheses Using the Myoelectric Signal. In Intelligent Systems and Technologies in Rehabilitation Engineering; Teodorescu, H.-N.L., Jain, L.C., Eds.; CRC Press: New York, NY, USA, 2000.

[53] Chan, F.; Yang, Y.S.; Lam, F.; Zhang, Y.-T.; Parker, P. Fuzzy EMG classification for prosthesis control. IEEE Trans. Rehabil. Eng. 2000, 8, 305–311.

[54] Phinyomark, A.; Phukpattaranont, P.; Limsakul, C. Feature reduction and selection for EMG signal classification. Expert Syst. Appl. 2012, 39, 7420–7431.

[55] Asghari, O.M.; Hu, H. Myoelectric control systems—A survey. Biomed. Signal Process. Control 2007, 2, 275–294.

[56] Jiang, N.; Dosen, S.; Muller, K.-R.; Farina, D. Myoelectric control of artificial limbs—Is there a need to change focus? IEEE Signal Process. Mag. 2012, 29, 152–150.

[57] Al-Mulla, M.R.; Sepulveda, F.; Colley, M. A review of non-invasive techniques to detect and predict localised muscle fatigue. Sensors 2011, 11, 3545–3594.

[58] Conforto, S.; D'Alessio, T.D.; Pignatelli, S. Optimal rejection of movement artefacts from myoelectric signals by means of a wavelet filtering procedure. J. Electromyogr. Kinesiol. 1999, 9, 47–57.

[59] https://statistics.laerd.com/spss-tutorials/friedman-test-using-spss-statistics.php

[60] http://support.minitab.com/en-us/minitab-express/1/help-and-how-to/modeling-statistics/anova/how-to/friedman-test/interpret-the-results/all-statistics-and-graphs/#p-value

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