Effect of time domain features on pattern recognition based myoelectric control

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MASTER THESIS WORK

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Copyright Statement

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Dedicated to my family;

TO MY FATHER

In a hope to meet you again in a place better than this world

May Allah give u a glorious place without any worry (Ameen)

Abstract

Electromyography is a technique of recording neuromuscular signals from muscles during movement and rest position. Recorded signals are in the form of electric signals which can be easily analyzed and studied. s-emg signals are recorded from the surface of muscles. They can detect any kind of movement in muscles which can help diagnose between a healthy and a disable person. s-emg signal are analyzed using different technique of signals and systems. According to a specific movement their behavior and pattern is noted, and further actions can be taken. Analysis of s-emg is beneficial for mankind. Signal analysis techniques are used to make computerized wheelchairs, robotic arms and food cooking machines for disable persons. In this research, pattern recognition and machine learning technique are adopted to analyze signals. 7-time domain features are selected for pattern recognition. Signals are combined in a group and analyzed by LDA. 7 features make 6 groups with different combinations of features. Data from 10 movements of hand and from 5 subject were collected in SMME EMG lab. Results after computation and feature extraction shows that as we increase the no of features, accuracy is improved up to the combination of four features together. As further by five feature combination accuracy increases up to combination of seven altogether. ANOVA test is performed to finalize results. These result show there is a significant difference in the mean of seven groups and features combination

Key Words: *Time domain feature, Linear Discrimination Analysis, pattern recognition, Surface Electromyography*

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CHAPTER 1: INTRODUCTION

Looking around us, it's safe to say that technology has taken over everything. We are completely surrounded by devices and are inordinately dependent on technology, from mobile phones to automatic and self-driven cars, from kitchen stoves to massaging sleeping beds, from daily life routine things to some medically advanced health achievement, all equipment are technology operated.

To elaborate more, we can see computers hacking all fields, be it engineering, medical, robotics or mechanics. In a revolutionary development of technology in different fields, it also covers a major spectrum of new techniques in the medical field which includes almost accurate diagnosis of many diseases, evidently surpassing human observational capabilities and even intelligence. Medical technology has also progressed in providing many alternative treatment options, which assist in managing patients. Furthermore, assistive technologies that help people with all kinds of disabilities, making them more independent of human care, like smart wheelchairs, hearing aids etc.

Talking specifically about physically disabled individuals, especially with missing limbs or other parts of the body, it has been greatly focused to assist them seamlessly. Imitation of neural signals, identified as electrical signals, have greatly attracted research for the past two decades. Humans produce different types of electrical stimuli like EMG, EEG, ECG etc. known as biomedical signals[1]**.** These signals have rich unrevealed information inside that can be highly useful in many aspects.

EMG (Electromyography) signals have information regarding motion of muscles in humans and can be utilized for benefiting individuals who lack or have lost extremities or have movement related problems. It can even be used to create robots that mimic humans. EMG data can easily be obtained, depending on the criteria of research you are interested in.[2]

The focus of this study is s-emg signals recorded by 10 types of hand movement.

s-emg signals analysis provides a profound depth of study than any other bioelectrical signals like EEG or EKG. The reason behind is, EEG, EKG is not concerning that s-emg have a variety of applications and data (gather from multiple movement, together or alone) and has gain its attention in variety of field.[3]

1.1 Background

We will deal with biomedical signals of EMG in this research. EMG (electromyography) records the electrical activity produced by the brain in response to or for causing movements in muscles. [1] EMG is a measure of contraction, relaxation and movement of muscles and it measures the extent of nerve conduction and observe any irregularities in muscle movement and contractions.[2]

EMG signals are collected from a nerve traveling from brain towards muscles called the motor nerve (MU), that is why EMG signals are also known as motor unit signals.[23] MU have almost 3-2,000 muscle fibres[40]. EMG measures speed and timing of conduction of motor nerve. Any irregularities either in timing or speed of conduction of motor nerve cause disability in movement. [2]

s-EMG are recorded for two main purposes, one is for the clinician to diagnose any illness which is known as diagnostic EMG, while the other is named as kinesiological EMG which is recorded to study literature and used for research.[40]Conduction phases, called as potential, during no movement, is known as resting potential, while during movement it’s called action potential. In resting state, charges inside the cell is more negative than the outside. Charge is normally -60 to - 100 mV inside and it remains constant until hand is moved.[4]

EMG signals can be recorded in two ways, surface/non-invasive EMG and invasive EMG. In surface EMG, electrodes are placed on naked skin and signals are recorded on the surface.[2] It is comparatively an easy approach but gives questionable results and requires a lot of processing. In contrast, invasive EMG has a needle like electrode which is injected inside the skin which is quite painful and complicated process but gives better accuracy and precision in muscle signals. [3, 4]

This research deals with surface EMG (s-emf) signals.

EMG can give better results and more fine signals. If the subject must perform required movement more than once, even for more accuracy, it is easily feasible.[5] Raw data of EMG should be as free of noise as we can manage and free of contamination from any kind of unwanted signals added during recording. Unwanted signals are noise that can be avoided by adopting standard recording techniques.[6]

Researcher gathers data from required muscles and required movements. These signals should be specific to each movement and record detailed information of chosen movements and the muscles involved. Despite all the adequate measures, during experiment noise may get into the original signal. As raw signal is huge and have noise in it, it is not easy to extract required information from it. To get all information from signal three main techniques are explained. These techniques explain EMG signal and it's extended of conducting, movements irregularities, muscles tone and strength of MU.

Pre-processing of signal is done as a foremost step to remove unwanted signal from raw EMG. However, pre-processing should be avoided in depth due to its destructive nature which damages the demanded data[10]. Next in removing garbage signals, we proceed towards feature extraction and selection in which required data from raw s-emg is collected. It is a most essential step in signal analysis as it gives masked and unseen information from raw data and gets rid of unwanted signals. Moving forward depends on selection of features as classification accuracy all rely on feature selection[11]. At the end signal is classified to identify the shape of signal and movement.[7, 8, 9]

There are many ways of classification, applied on different types of bio-signals by researchers, to check accuracy for better signal identification. Two of these are artificial neural networks;(ANN), linear discrimination analysis (LDA). Quadratic discriminant analysis (QDA) and support vector machine, already tried by researcher for EMG signals, and gives a very small difference in their classification accuracy for a biomedical signal [12, 13.14.15].

Selection of methodology for classification should be made after careful evolution of its accuracy and performance on different types of movements and to compare the movement of normal and handicapped person. LDA classifier is easy to implement and gives a little more accurate results in comparison to other classifiers.

For classification that control prosthesis of less or no of movement two types of modules are purposed, Amplitude Modulation and Frequency Modulation: their choice of implementation depend upon researcher their investigation and study design. If alteration in joint of finger and wrist is the main concern, every researcher prefer mean frequency modulation.[16] If not, then Amplitude Module is the next choice for classification covering joint angle of hand.[17,18] Any change in muscle fibers (either in shape or consistency of muscles) around the joint or either change in orientation of angle also alter the movements, hence, electrode placements site should be arranged according to change.[16] Hand prosthesis, wheelchair and virtual mousse are available and are electrically controlled by patients having MU disorder or amputee hands.[19] EMG signal

analysis also help patients having problems in conduction of MU to grasp easily.[19,20]. Many methods have been developed to help disable persons having a high level of amputation, while for smaller disabilities more work is done to analyze signals with great precision .
This thesis is based on the movement of hand.

1.2 Extent of this research:

Scope of this research is given below.

- Only 10 hand movements are considered in this research and muscles, related to hand movement, are studied. Reason of selection of hand muscles despite of many other muscles is because they were easy to record and easy to perform movement.
- Research is useful for a patient with amputee hand or arm, for artificial hand they can do daily routine tasks without any hurdles.
- This is also helpful to make a robotic arm imitating human.
- Band like sensors (electrode) were used in this research for data recording because of its ease and comfort to patient.
- For classification of EMG data linear discriminant analysis LDA is applied.
- This research benefits robotics, physiotherapist, medical and biomechanics for designing instruments and equipment's for patient's ease.

1.3 Motivation

The center of this research is to study s-emg signal in depth and make it useful in the real world.
s-emg signal contains a lot of information of brain signal and movements of muscles. It also contains information regarding timing and muscles tone, as already mentioned. This information can be very beneficial if interpreted carefully and accurately.
People's efforts to make life easy and facilitate humans, have continued since ages. As we know around the globe its high prevalence of accident and for this reason many of us have amputee extremities, commonly described as disabilities in catching brain signal. It is estimated that roundabout 5000 individuals lost their arms in a year.[21] Disabled persons also generate signals from the brain like normal person, but these signals are weak and irregular, which can be recorded (Walker et al.1998).[22] For this we need to classify the signal in a better way to get more information

and design a software that helps patients who lost their limbs that they may perform routine work with, with artificial limbs. S-emg signal information is also helpful in designing a robot that mimics humans in all aspects, help us in medical methodologies, doing complicated surgeries, and in many other tasks that need minor details.[17]

1.4 Problem Statement

As already mentioned, s-emg signals are complicated and have huge hidden information recorded in a millisecond. Even then, comparatively with other bio signals like EEG EKG EMG signals, they are easy to analyze due to their large amplitudes and frequencies. Other signals have smaller amplitudes and mostly their recording processes are quite complicated.

In a perfect environment, perfect experimental conditions during recording of s-rmg signals, s-emg still gets some noise in it that alter the shape of signal and information. It should be kept in mind while dealing with any bio-signal that you can avoid noise all in all. Therefore, a system with noise free data acquisition should be designed or a software that gives noise free signals should be implemented before signal processing. Noise in s-emg can be interference from many sources like power lines, radio signals, unnecessary filtering or any other source. Other factors like skin resistance, electrode quality, location of electrodes and other devices and cables used in the system also add up to the noise content.

Apart from noise, we also have different signals from different individuals. Every human has its own specific signal and different from others, so it makes classification process contentious.

Feature extraction is the main pre-processing of EMG signal in (pattern recognition) based classification, by selecting features for EMG signal the accuracy of classification is affected. In this study we evaluate different features performance on EMG classification

1.5 Purpose

Purpose of this research is as under

- Record s-emg data and pre-process it to remove noises.
- s-emg data, free from noise, to be further analyzed for feature extraction and classification.
- To differentiate different movement by feature extraction and selection approach.

- To analyze output data from classifier LDA and discriminate different types of signals, thus differentiating movements.

CHAPTER 2: LITERATURE REVIEW

As mentioned in prefatory that surface EMG collect signals from electrode placed on the exposed skin (surface) of required muscles, whose movement must be measured. s-emg records electrical stimuli generated from brain, nerves in the brain also generate signals in handicapped individual without any kind of external device, as that in a healthy individual[22]. These signals may be weak and irregular but are recordable. These recorded EMG signals have information that can be further analyzed to get useful and reliable information from raw s-emg signal[23]. Different techniques were implemented on input raw EMG signal to get pattern recognition and classify the different movement from the signals. Different classifier has a different accuracy of recognizing movement of arm. 10 types of movements are acknowledged with an average accuracy of 80 to 90%[24] and it maximizes up to 90%.[25, 26]

Scientists are working from many years to make a device that works exactly like a human. Fabricating a device for handicapped patients, to facilitate and support in performing necessary tasks, to live stable life as healthy one. Initially, researchers worked on open and close hand grip and control movement, but now they can control multiple movement of limbs. Previous Studies are conducted on 17 subjects, 11 healthy and 6 disable persons, and only 12 different types of movement are considered, hence gives, dubious results[27]. Even through incredible achievements and unbelievable results there is still a room for improvements and reach towards new level in control of s-emg signal.

To build robotic arms or devices that work perfectly like humans, we need multiple movements and huge amount of data with maximum accuracy and control. For further research, to recognize the validity and accuracy of classification method and to compare different classification methods, researcher may need some standardized data set which is freely available for everyone[29, 30]. Even though we have achieved a lot of progress and advancement in the field of automation, we still acquired ineffectualness in this field when it comes to implement for ease of society[28]. Many authors write about the importance of available data set which have definite value and is freely accessible to public.

s-emg / motor signals are mainly collected as two forms static (a constant position without any movement) and in a motion (when performing a movement e.g. walking, waving). From the previous studies it is found that when we deal with both type of movement stages, at the same instant we have good achievements.[31, 32, 33]

As we already know change in position, any kind of movement causes large amount of disturbances in signal hence, it may be reduced by recording different types of position in a constant state holding hand still in place. Studies were conducted in motion-free posture; three static[34] postures, five[35] and another five static posture[36] used to train the classifier. Some of the hand movements are influence by body position and vice versa, so classifier should have process s-emg signal with dynamic motion. Both static and dynamic motions are investigated together in researches for classification and control, total 7 types of hand movements are analyzed, from which four of them are in static phase and three are in dynamic phase[37]. Classification accuracy dependent upon data set and movement's type and numbers.

NinaPro (Non-Invasive Adaptive Prosthetics) data set is the largest data set available openly for public with free access. This data set have 27 subjects as volunteers and recorded 52 types of movement of arm which is repeated during recording process. This data set have some healthy individual arm movement too for accuracy comparison.[38] Computer based arm and robotic arms are designed for betterment of patients.

As we already know despite the astonishing achievements and development in robotics domain, where human eye is amazed by its unbelievable results of artificial prosthesis and robots that work mechanically well and almost perfect hardware design but, they all have limited working ability. In control movement, still more work is required to be done in this field to mimic human hand movement and more control. Scientist need more accurate classification method that gives information about more myoelectric movements, precise control of motor nerve and required results. Great deal of work and time is required to reach the perfection in the field of robotics and having as accurate movement as human hand.

As already mentioned, different research follows same method as other already introduced, data acquisition, pre-processing, Feature extraction and classification by machine learning process.

Data collection methods also effects the end results. For better data collection, accurate positions and number of electrodes are required.

In this research similar steps are followed for data collection, Pre-processing. But focus is on feature extraction and classification method of motor signal of hand movements.

Feature selection is a crucial step in research for the study of EMG, it must be kept in mind before selection of features that what type of data are we dealing with, for example movement due to force on joints[40] and motor nerve function symbolized by different types feature[39]. Features extraction can be observed in three groups, time domain, frequency domain and time frequency domain. Frequency and time domain features are easy to approach and required less time and hardware step while 3rd type is comparably tough to be handled and requires extensive detail at same time. Before dealing with time frequency domain we must apply some data reduction programming technique[41, 9]. Application of both time and frequency domains together provide better results in EMG signal recognition[42, 13]. Other researchers deal with almost 37 features of time and frequency domain.

Time domain features are considered in this research.

From study of previous record it is found that no approach of feature extraction of s-emg data is accurate and precise[11, 43, 44]. Different studies are carried out to investigate reliable method of feature extraction and results are compared and further investigated by final clustering and classification. Difference in results were presented due to variability in classification method and input data. Input data variations occur mainly due to hardware setup, noise (internal/ external) and position of electrode Etc. These differences can be reduced by applying more than one classifier while processing data.

Results are highly depended upon the feature selection rather than classification approaches. Different method of classification are utilized, compared and investigated for accurate results in literature which were LDA (linear discrimination analysis) [42, 13] ANN (artificial neural network), k nearest neighbours[44] and SVM (support vector machine) [26,] Hudgins et al, worked on ANN classifier to distinguish 4 types of hand movement and before classifier he analyzed input EMG signal by time domain features[12]. Comparison of five different classifiers is made by Hargrove et al in his work and give results of almost same performance of each classifier[44].When LDA and SVM classifier are compared for their efficiency by Lorrain et al. and it also gives similar results. In this study, time domain feature extraction and autoregressive were focused[32].As further investigation are continued, it is clear that classification greatly impacts accuracy of results[45]. Linear and nonlinear classifiers are used in different studies and are compared for their efficacy and accuracy. Nonlinear algorithm is more efficient than linear algorithm.

This research contains work on 10 different hand movements collected from 5 individuals. Different time domain features are selected and implemented, and results are validated by LDA classifier. In this research, feature selection and performance of LDA is thoroughly analyzed.

Feature selection is a crucial step in signal analysis[5] because, it saves the information, which is required and important, for recognizing the posture and eliminates unwanted part of the signal.[8]

Time domain features are most commonly analysed in many researches. These features can detect muscles force exerted during movement, while now a days some authors also focus on frequency domain feature extraction, which are capable of detecting muscles fatigue during movement[10, 46].Fatigue in muscles situate in frequency domain of signals thus literature shows to analyze frequency domain features, athematic mean and median frequencies are most commonly selected features to analyse[47, 48]. Studies shows that continually high output of MDF and MNF have large muscles force.[49]. While other studies have completely opposite conclusions[50, 51,] that is that there is no relation between force of muscles and MNF and MDF[52, 47]

LDA is most prevalent method to be used now a days for pattern reorganization[53]. Other than signal analysis LDA is used in many fields for reduction of dimensions and feature extraction such as it was used in recognizing tumor (cancer) cells in brain tissue[55], in differentiating in faces and in speech[54,56,] it also help in classification of text[57]. LDA takes as it is information and a lot of high dimensional highlights are assembled into classes by finding an ideal change (projection) that maps the crude highlights into a lower-dimensional space while protecting the class structure. It limits the inside class separation and all the while amplifies the between-class separation, in this manner accomplishing greatest segregation. This change is promptly figured by applying the eigen-deterioration on the dissipate frameworks of a preparation informational index[58].

As researchers continue to experiment methods to get more and more better results, many new algorithms are come to know based on LDA algorithm i.e., Uncorrelated Linear Discriminant Analysis (ULDA)[59] Orthogonal Fuzzy Neighborhood Discriminant Analysis (OFNDA) [60], Generalized Discriminant Analysis (GDA) [61], and a combination of LDA, Fuzzy Logic and the Differential Evolution optimization technique(DEFLDA)LDA and NLDA is compared for class separability LDA gives better results.[63]

In this research simple linear LDA is used for data analysis

CHAPTER 3: METHODOLOGY

s-emg signal is a complex signal and difficult to be analyzed because of the interruption of various types of noises, as these signals move through body tissues. Similarly, s-emg 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 s-emg signals thus disturbing the analysis process[64.] That is why these signals need to be processed and filtered to remove unwanted additions and make them reliable for further processing.

Purpose method for the s-emg classification is:

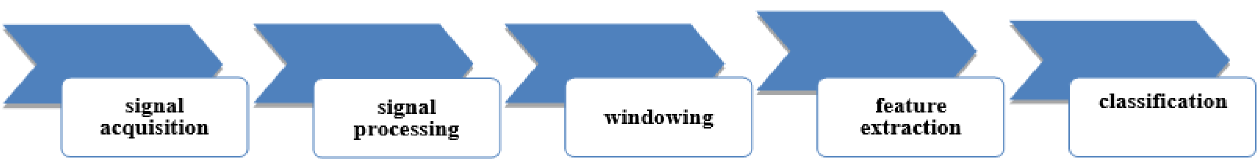

Figure 1: Proposed Method

3.1 Data Acquisition

Data is collected from 5 individuals by an array of 12 channels. Experimental setup is designed with full consideration to avoid any mishap and interference. Before experimenting and data collection, all individual is trained about movements and cautions during recording sessions. Proper measuring instructions are followed. Skin is prepared and the subject is subject to remain static and allow only one movement which is required. Bipolar Silver/silver chloride electrode are used for signal detection. Data is sampled with frequency of 8000Hz. 10 different hand movements are asked to perform by subjects for recording, each movement is performed for 5 seconds with interval of each movement is 5 sec (rest period). For a new movement every participant must rest for 13 seconds, this rest helps to avoid any irregular movement and incomplete data collection. Data collection is spanned over 2 weeks, each data individual performs all the tasks 4 times. 60db amplifier is used for data amplification. Data is stored for analysis of further steps. Before data patterning all rest, stages are removed from data.

Placement of electrode is done with caution and using standard protocol. Maximum signal of s-emg available and detected at the muscle 's belly away from tendons so electrode is placed on it. For multiple electrode distance between electrodes caution is taken that they aren't more than 2cm.

3.2 Data Description

Movement:10

Sampling frequency: 8000Hz

Subject: 5

Movements are open hand (oh), close hand (ch), extension of wrist (ew), flexion of wrist (fw), pronation (P) and supination (S), Side Grip, Fine Grip, Agree Pointer

3.3 Pictorial Representation of 10 hand Movements

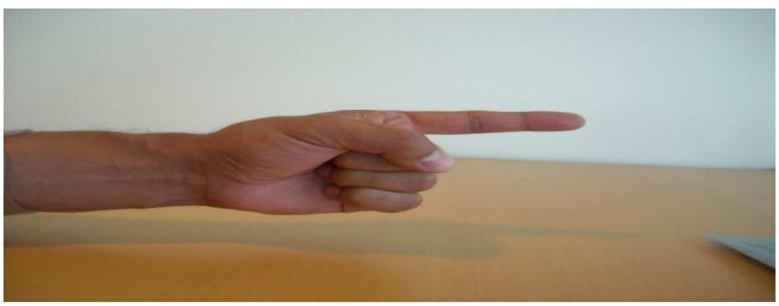

Figure 2: Pointer

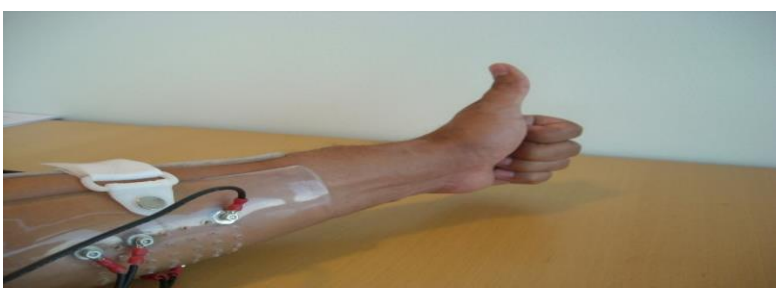

Figure 3: Agree

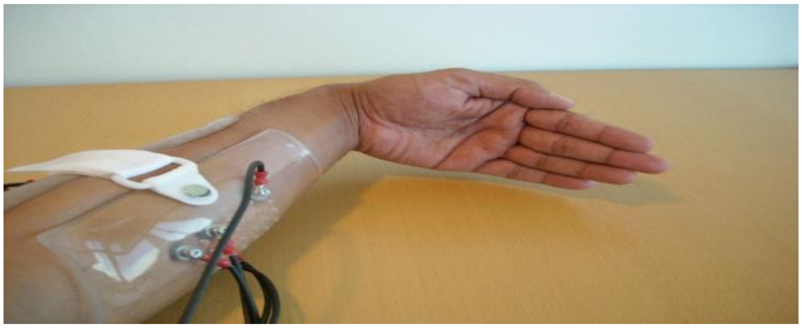

Figure 4: Flexion

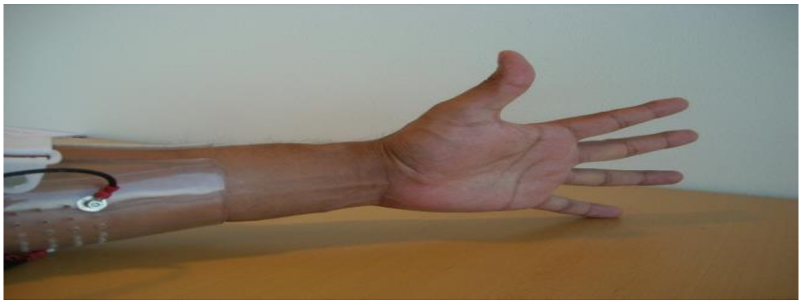

Figure 5: Open

Figure 6: Pronation

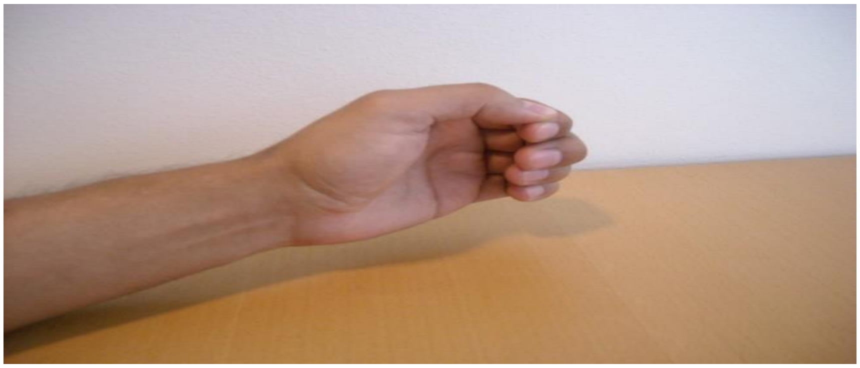

Figure 7: Open Grip

Figure 8: Relaxed Stage

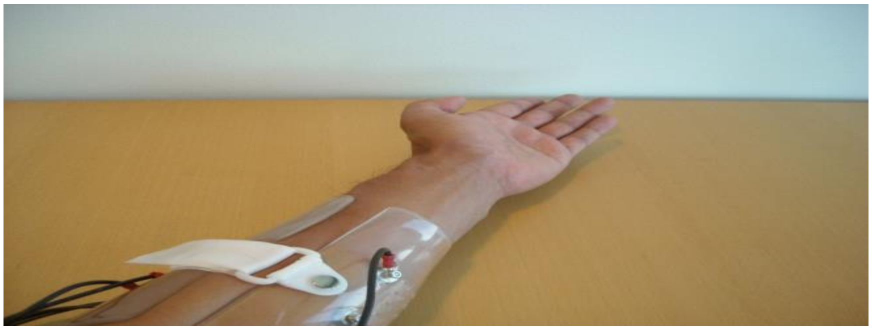

Figure 9: Supination

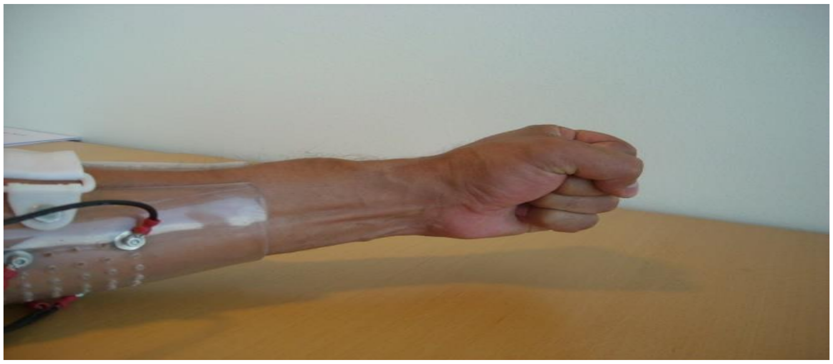

Figure 10: Close hand

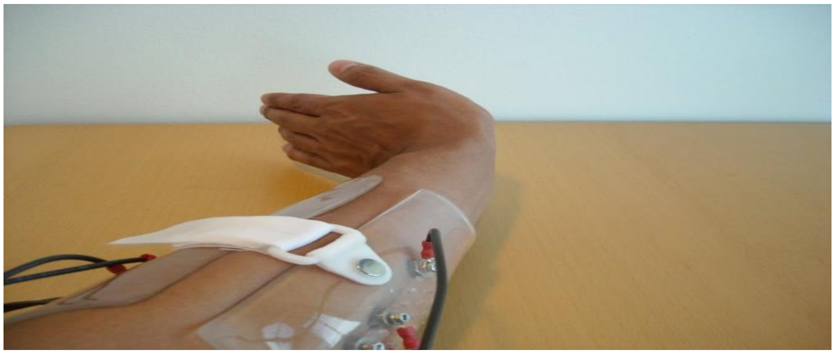

Figure 11: Extension

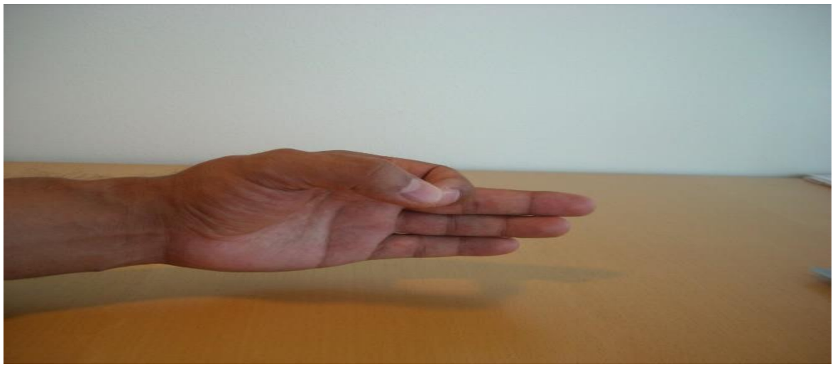

Figure 12: Fine Grip

3.4 Pre-processing

As we already know s-emg signal carry huge amount of noise. Before signal analysis it is better to remove unwanted signal from actual desired signal. Most of noise is absorbed during recording phase of s-emg signal. So, to avoid this, ideal experimental conditions should be performed. Careful placement of electrodes and skin thickness should be kept in mind to avoid any error. AG/AGCL electrode are proved to be good in reducing noise to signal ratio during recording.[64] Tangled and improper use of recording machine should be checked and avoided and maintain proper arrangement and configurations of wire and system to reduce chance of noise attachment with signal. Positioning of electrode should be precise and ideal. Although all the precatory measure used in recording of s-emg signals, noise still make it way to harm actual signal either by external through environment or internal thorough another biomedical signal recording along s-emg. By increasing SNR ratio signal can be made free from noise. Noise removal is a crucial step in signal analysis, if this step is omitted, end results will be adverse[64.65].

Firstly, all data collected is peaked between frequency range of 50hz to 500 Hz, and then applied with a low pass filter down at only 20Hz. Preceding this, data is processed to make it garbage free, a necessary step as to remove the noise that is collected while the hand shifts from the state rest to motion continuously. To do this, every movement is partitioned into three, discarding first and the third parts so that only the middle remains for collection. This step is taken into further processing of the middle part in a way that all the data is averaged, and single sample is selected from each movement's reoccurrences. All in all, each movement have ten samples with ten reoccurrences. Hence, everyone's data for s-emg is normalized at zero mean and standard deviation as[66.67].

s-EMG raw data of subject one and 10 different movement is below:

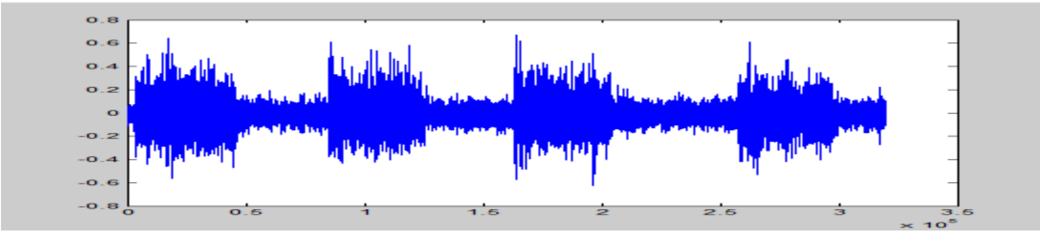

Figure 13: *Movement 1, Open hand*

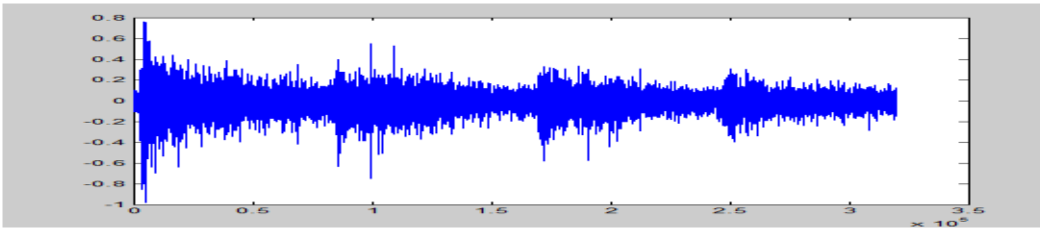

Figure 14: *Movement 2, Close hand*

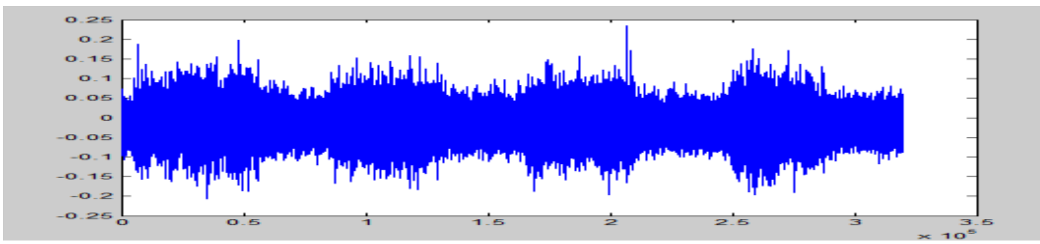

Figure 15: *Movement 3, Flex hand*

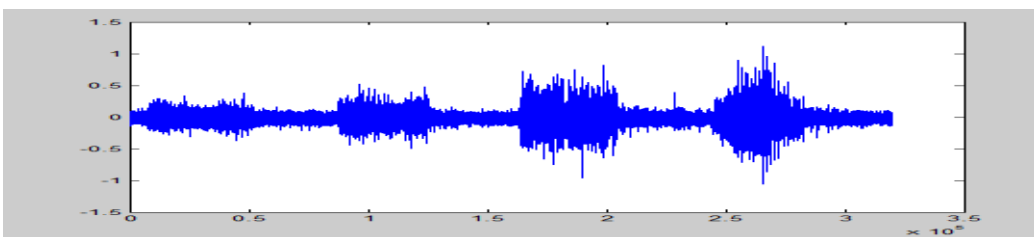

Figure 16: *movement 4, Extend hand*

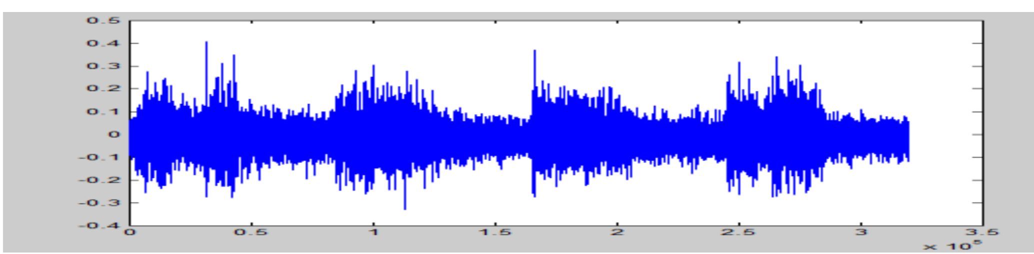

Figure 17: *Movement 5, Pronation*

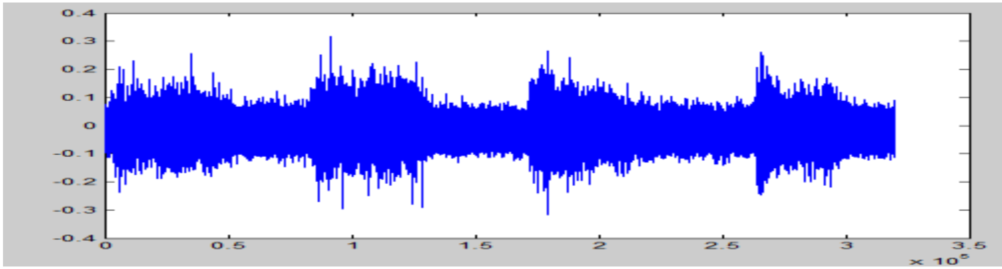

Figure 18: *Movement 6, Supination*

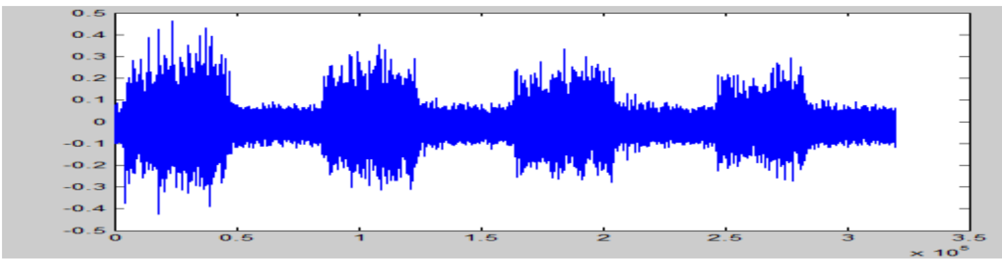

Figure 19: *Movement 7, Side grip*

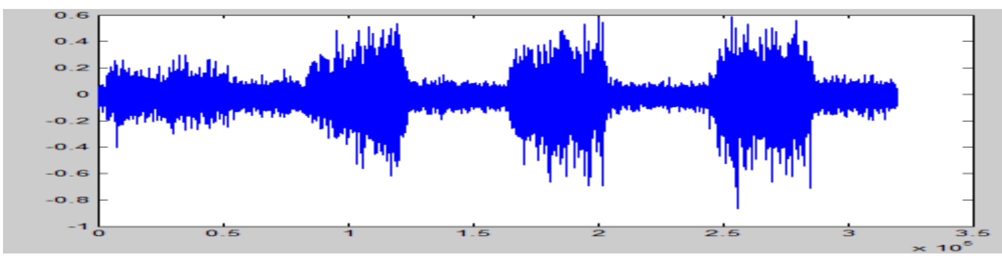

Figure 20: *Movement 8, Fine grip*

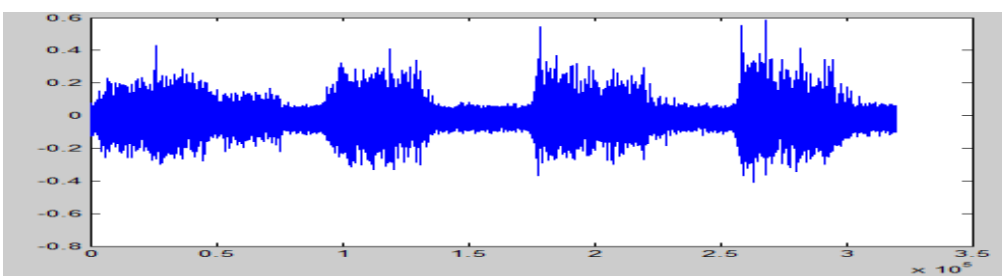

Figure 21: *Movement 9, Agree*

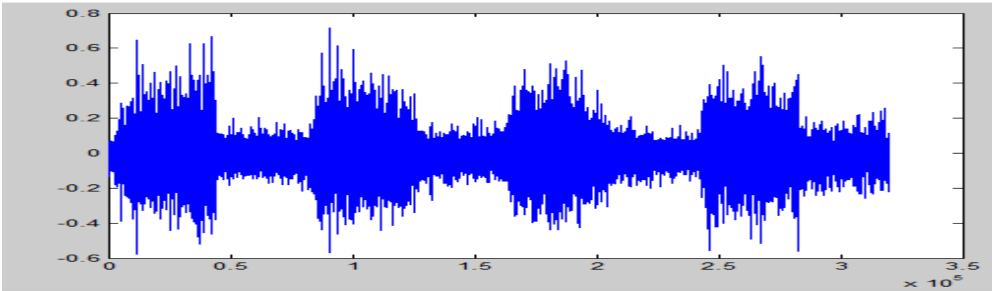

Figure 22: *Movement 10, Pointer*

3.5 Pattern Recognition

I. **Windowing**: The collected feed data is further processed by a sliding window analysis concept. The window is kept at a size of 0.25ms and interval step is kept half as that of the size. This gives better results as to a simple windowing technique for effectively capturing the clustering of data. In each intervals of the sliding window, feature extraction takes place and the results are collected.

II. **Feature extraction**:

Following noise removal technique s-emg signal is further processed by feature extraction system. Features techniques is applied to get rid of extraneous data and getting appropriate and pertinent information from the raw s-emg data. Accurate and precise selection of feature for raw s-emg data gives desired output and information. It should be kept in consideration that any classification method for s-emg signal does not give maximum output without feature extraction prior to any kind of classification. Thus, we should calculate feature vector to make classification results more accurate and precise. Although other properties of features and classification should be acknowledged like computational cost, robustness, complexity etc. and should never be ignored[68]. Careful selection of features should be performed as classification results are highly dependent on feature selection.

Features extraction are of 3 types, depend upon domain of its working: time domain, frequency domain, time frequency domain[5.9]. This research deals with 7-time domain features.

Time domain feature are more efficient and easier to analyze computationally without any need of complicated hardware design. They reduce raw s-emg dimensionally as well.

Whereas Time Frequency Domain features need a lot of information and extensive hardware system for calculations[11, 69]. Frequency domain features are best to study fatigue in the s-emg signals.

Features selected for this research, with their descriptions are as:

- Mean absolute value (mav) [8]

  Most common feature in s-emg signal analysis. It is a moving Average of absolute value of s-emg signal amplitude. It is also known average rectified value, averaged absolute value, integral of absolute value, and the first order of v-Order features.

$$mav = \frac{1}{N}\sum_{I=1}^{N}|X_i|$$

N = total length of EMG signal
Xi = EMG signal in segments/index i

Its initial index detection in s-emg signals for prosthetic and robotics arm.

- Willison Amplitude (wa)[78,8]

  It is related to muscles contraction and stimulus speed of motor nerve.

  wa can be explained by a threshold value which is predefined and measure change in s-emg amplitude with respect to that threshold value.

$$\mathbf{wa} = \sum_{i=1}^{N-1}\left(\int([x_n - x_{n-1}])\right);$$

$$\int(x) = \begin{cases} 1, & if \quad x \geq threshold \\ 0, & otherwise. \end{cases}$$

  We gain frequency information from wa

- Zero crossing (zc)[79]
  zc it counts no of times amplitude crosses y-axis. It Gives count values of amplitude change from positive to negative and vice versa. Threshold decided to avoid background noises in s-emg signal.

$$zc = \sum_{i=1}^{N-1}[sgn(x_i \times x_{i+1}) \cap |x_i - x_{i+1}| \geq threshold\ ];$$

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

It is a time domain feature and gives information related to change in frequency with time.

- Waveform Length (wl)[73,11]

It can be defined as cumulative length of motor signal over a segment of time. It results shows frequency, time and amplitude value.

$$\mathbf{wl} = \sum_{\mathbf{i=1}}^{\mathbf{N-1}}|\mathbf{x_{i+1}} - \mathbf{x_i}|$$

It tells us about how complex the signal is.

- Slope Sign Change (ssc)[80,12]
  ssc is quite like zero crossing it measures the change in sign (negative, positive) in the slop of waveform. A specific threshold is defined to avoid background noise.
  $$\boldsymbol{ssc} = \sum_{i=1}^{N-1} \left[\int [(x_i - x_{i-1})] \times (x_i - x_{i+1}) \right];$$
  $$\int (x) = \begin{cases} 1, & if \quad x \geq threshold \\ 0, & otherwise. \end{cases}$$
  By this we can estimate frequency roughly.
- Myopulse Percentage Rate(mr)[78,20]
  Mypulse output average value is known as mr. can be define as one when absolute value of s-emg signal is more than the predefine threshold value.
  $$\mathbf{mr} = \frac{1}{N} \sum_{i=1}^{N} \left| \int (\mathbf{xi}) \right|;$$
  $$\int (\mathbf{x}) = \begin{cases} 1, & \mathbf{if} \quad \mathbf{x} \geq \mathbf{threshold} \\ 0, & \mathbf{otherwise}. \end{cases}$$
- Cardinality(cd)[80]
  Distinct value in a set can be called as cardinality. One should follow two steps to compute cardinality from a data set. First data should be sorted, and one sample is distinct from the next if the difference is above a predefines threshold

  Step 1 $\quad y_i = sort(x_i), i = 1$
  Step2 $\quad cd = \sum_{i=1}^{N-1} |y_i - y_{i+1}| > \in$

3.6 Combination of Features

These features are combined to gather and classify for better results. By statistical combination formula combinations of features were made and their behavior on classification accuracy is observed. Combination formula is given below:[83]

N = n! / R! * (N - r)!

Where n represents the total number of items, and r represents the number of items being chosen at a time.

! = Factorial 4! = 4 * 3 * 2 * 1

in this research n is 7 and remain constant while r will be 2 3 4 5 6 7.

features are combining in two three and up to seven together and their impact on classification accuracy and pattern recognition is observed.

3.7 Classification Method

Classification of signals and pattering of data solved many questions in the field of engineering and science. It has also helped in diagnosis of medical diseases. For use in medical, the methods need to be simple, fast, accurate and precise. s-emg signal classification helped in making human like robots, artificial limbs and other computer-controlled machine-like wheelchairs. As already mentioned, motor signals of disable people is different from healthy individuals, thus by differentiating both signals we can estimate and diagnose loss of muscle tissue and neural signals of brain. Fatigue of muscles can also be classified and has its best applications in sports science. Accurate feature extraction and selection and after that classification of s-emg signal can have a remarkable difference in a disable patient who has limited movement of either limb, in comparison to a healthy individual.

In previous researches, many types of classifiers were introduced for s-emg signal classification. These classifiers are pertinent to s-emg signal for numerous analysis. These classifiers are support vector machines (SVM), artificial neural network (ANN), linear discriminant analysis (LDA) and fuzzy classifier. [81]

As previously mentioned, feature extraction is a compulsory step before application of classifier, as their results' feature vector, it acts as an input for a classifier for signal recognition of shape and motif of signal.

EMG signal is a signal from neural activity from brain that allow muscles to move in multiple direction, that’s why EMG signal is quiet tortuous and not easy to read and interpret, hence it is necessary to be reduced dimensionally before application of any classifier. Reduction of dimension give benefits of less working time of software with less load. LDA and PCA are mainly used for reduction but they take a lot of time for analyzing signals, but for the betterment of their work, scientists did discover new algorithms.

In this study LDA classifier is used to classify available data into classes. LDA classifier is a robust type and is already been used in many researches. It can be applied on both type of data binary as well as multi class classification. (LDA) classifier gives almost accurate classification and from this many feathers’ projection methods are compared. Many recent works have been published on LDA. However, PCA, with other techniques, also provide classification accuracy.

Classifier can be a linear and non-linear, as name implies, linear discriminating analyses (LDA) is a linear classifier and it uses dimensionally reduction method. For its ease of use and efficiency in real time data, LDA is selected for this research to classify s-emg signals.

linear discriminating analyses (LDA) is also known as normal discriminating analyses and discriminating function is used linear combination in feature to find different object and classes. Application of LDA is in statistic, pattern recognition and in machine learning.

LDA picks new dimension for to data either by maximum separation between the mean of class or minimize the variance within the selected classes.

diagrammatically representation of work principle of LDA is given below for the multiple classis's separation[84]

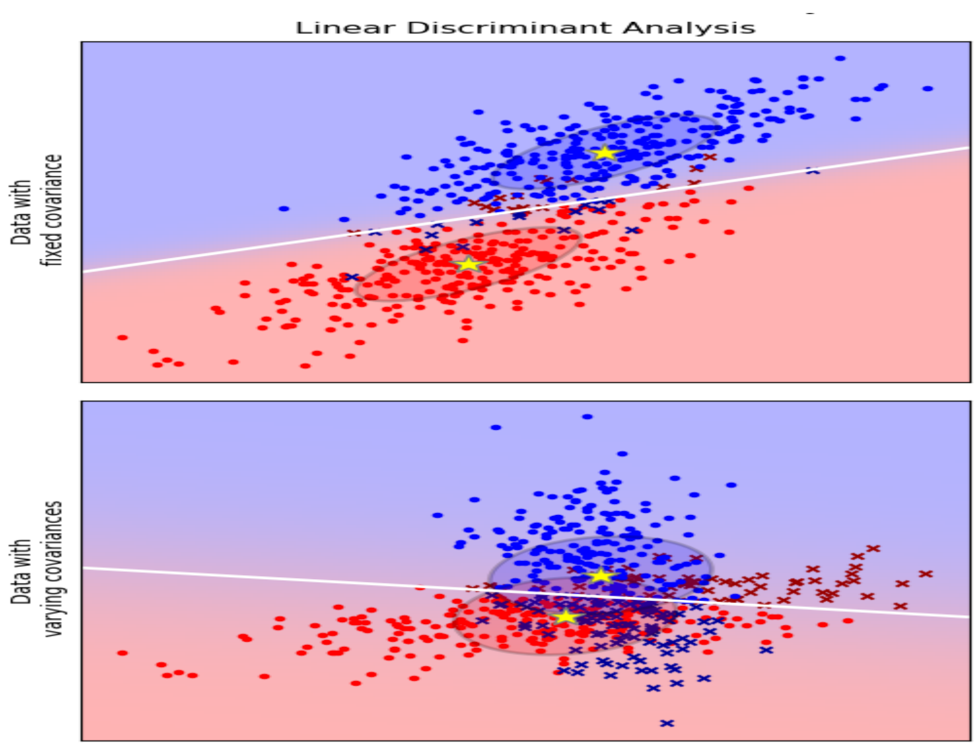

Figure 23: LDA (Linear Discriminate Analysis)

CHAPTER 4: RESULTS

First, Seven-time domains features are computed and analysis for their effectiveness in s-emg classification accuracy. These seven features are compared alone and in groups. Seven features are computed for accuracy and precision in classification which are Wilison Amplitude (wa), Waveform Length (wl), Cardinality (cd), Mean absolute value (mav), Slop sign change (ssc), Zero crossing (zc) and Myopulse output rate (mr).

after study of single feature, features are grouped together in two, three and up to seven features and analyzed and compare for better performance and accuracy in detection of motor signals.

LDA classifier is implemented to access accuracy in features. LDA work to reduce dimensions of s-emg. LDA output a definite number and it analyses both binary and multi class classifications we briefly discuss the theory of RNNs, key differences to popular ANNs, its relevance to financial data and the proposed method. Financial parameters and features are in general non-linear, highly correlated and temporal in nature i.e. correlation is not only valid for a single time instance (static) but also over multiple time steps. Variation in one parameter can cause other parameters to fluctuate and therefore affects the overall output or contribution towards bank's survivability. For example, if there is a positive change in the liquidity ratios of a bank it implies that the bank is refraining from investing the capital thus in the longer run it will have a negative impact on the earnings of the bank. Another example is that if the earnings of certain bank are low, it implies that the bank suffered loss or relatively lower profit in its investments. This loss has a negative impact on the capital as it is recovered from it at the end of the year; this process is known as capital erosion.

4.1 Comparison of Seven Features

4.1.1 Signal Feature Accuracy

When Signal features are computed gives maximum of 68.88% mean accuracy from the Waveform Length (wl) feature. Minimum accuracy is obtained from Cardinality (cd) feature Below is the table of accuracies and mean value of accuracy for all the five subjects and seven features.

Table 1 Seven features verses five subject accuracy in percentage

		wa	wi	cd	Mav	ssc	Zc	mr
subjects								
1	Accuracy percentage (%)	68.52	78.85	40.8	78.36	66.23	60	75.73
2		44.88	62.78	30.43	53.93	57.04	43.44	53.6
3		44.26	62.78	30.43	53.93	57.04	43.44	53.6
4		75.24	76.55	35.83	75.24	70.32	52.62	79.5
5		46.28	63.44	47.73	63.11	48.52	53.27	58.82

A graph has been plotted between subjects versus accuracy for each feature which is given in the figure (24). Graph provide a comparison between accuracies of different features with same subjects. For instance, wl (Wilison Amplitude) provides the best accuracy for all subjects except subject 4. mr (Myopulse output rate) has the best accuracy for subject 4. wl has also greatest average accuracy and cd has least average accuracy

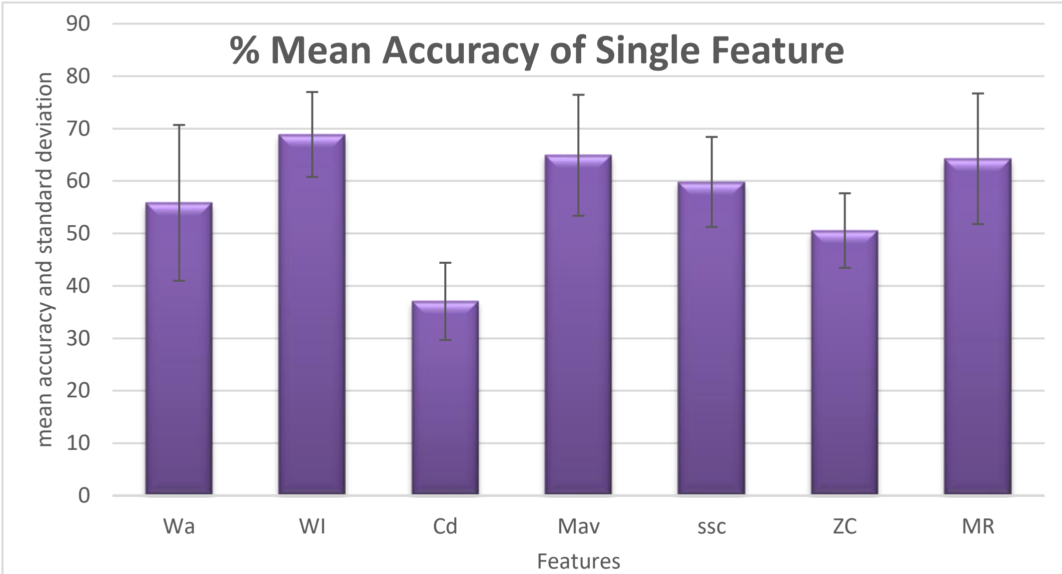

Figure 24 : Percentage mean accuracy of single feature

4.1.2 Combination of Two Features:

Group of two feature is made and tested for accuracy. By grouping each feature with every other one 21 groups have been made. In that case we have noticed an increase in the overall accuracies. When features are combined with other feature, better accuracies have been achieved rather than when their accuracies were calculated individually. For example, WA has accuracy of 68 while ZC has accuracy of 60 and together they provide 74.75 percent accuracy. Different groups have maximum accuracy against different subjects (e.g. WA+WL has maximum efficiency for subject 1 and ZC +MR has best accuracy for subject 4) but WL +SSC has maximum average accuracy of 70.78 percent. Given is the table of grouped features accuracies.

Table 2 21 combination of features verses five subject verses percentage accuracy

	subjects		1	2	3	4	5
No#			Percentage accuracies				
1		wa+wl(%)	76.88	60.82	60.82	80.82	61.31
2		wa+cd(%)	61.47	40.81	40.81	75.24	43.93
3		wa+mav(%)	77.04	57.04	57.04	79.62	61.96
4		wa+ssc(%)	69.67	46.72	46.72	77.04	47.7
5		wa+zc(%)	74.75	54.42	54.42	81.31	61.14
6		wa+mr(%)	70	48.52	48.52	76.72	53.93
7		wl+cd(%)	78.85	62.78	62.78	76.55	63.44
8		wl+mav(%)	79.18	61.14	61.14	76.55	63.11
9		wl+ssc(%)	77.04	65.08	65.08	81.96	64.75
10		wl+zc(%)	79.5	63.6	63.6	76.88	64.75
11		wl+mr(%)	78.85	63.44	63.44	82.62	65.08
12		cd+mav(%)	70.32	51.47	51.47	69.34	56.39
13		cd+ssc(%)	28.52	24.26	24.26	21.63	16.88
14		cd+zc(%)	60	43.44	43.44	49.01	53.27
15		cd+mr(%)	37.54	26.55	26.55	40.49	33.44
16		mav+ssc(%)	77.04	61.63	61.63	79.34	62.45
17		mav+zc(%)	79.18	55.73	55.73	76.72	65.9
18		mav+mr(%)	77.86	57.54	57.54	80.81	64.09
19		ssc+zc(%)	74.75	61.47	61.47	82.78	60.32
20		ssc+mr(%)	67.86	55.4	55.4	71.8	48.36
21		zc+mr(%)	80.32	56.22	56.22	85.08	67.21

I.e.: horizontal line represents subjects

vertical line: different features combination

accuracy is in percentage

A graph has been drawn to compare the accuracy of each group against single subject. Graph has been shown in figure (25).

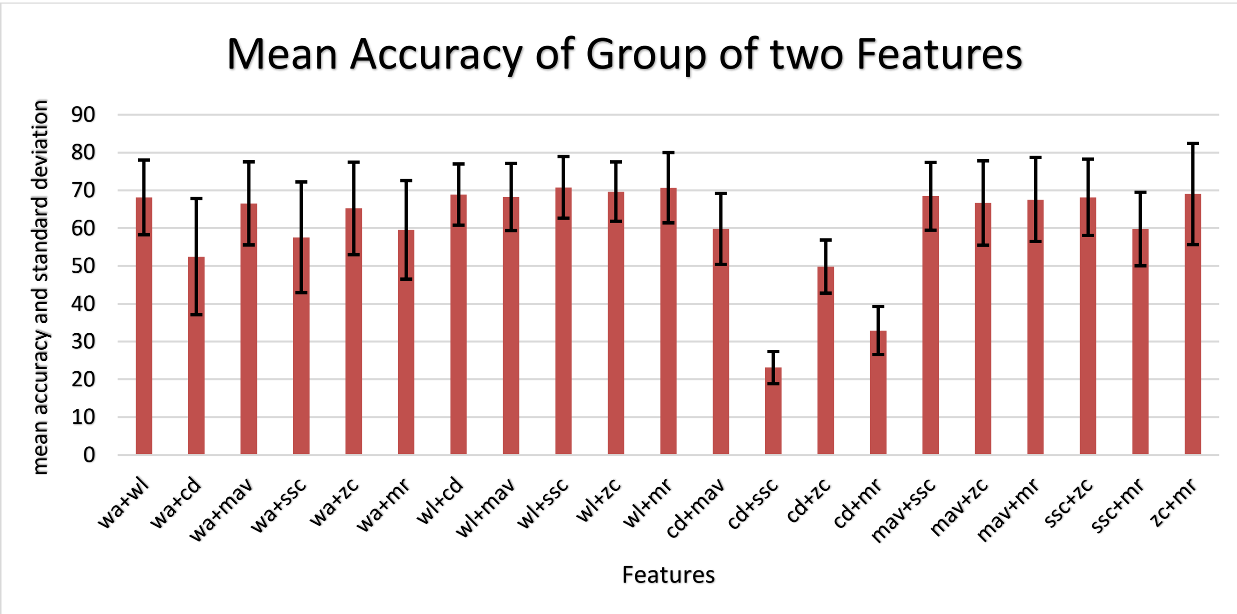

Figure 25: Mean percentage accuracy of group of two features

4.1.3 Combination of Three Feature

Three features are grouped together, and 35 groups have been made and tested for accuracy. There is a 4 percent increase in average accuracy as compared to group of 2 features. WI, MR and ZC together provide maximum average accuracy of 74.126 percent. Given is the table of grouped features with best average accuracies while graph in figure (26) shows the comparison of accuracy of every group against subjects. Improvement in the accuracy can be easily seen in graph and there is no group of features as an outlier.

Table 3 Percentage accuracy of groups of three vs five subject

subject				1	2	3	4	5
No#				Accuracy in percentage				
1			wl+wa+cd(%)	76.88	60.81	60.81	80.81	61.31
2			wl+wa+mav(%)	76.55	59.01	59.01	80.49	61.63
3			ml+ma+ssc(%)	77.37	59.83	59.83	81.8	61.8
4			ml+ma+zc(%)	79.01	65.9	65.9	84.26	70.49
5			ml+ma+mr(%)	78.03	59.34	59.34	81.63	61.8
6			wa+cd+mav(%)	78.03	59.34	59.34	81.63	61.8
7			wa+cd+ssc(%)	72.78	54.91	54.91	77.86	54.59
8			wa+cd+zc(%)	63.27	46.55	46.55	75.9	45.24
9			wa+cd+mr(%)	62.29	43.11	43.11	75.57	46.22
10			wa+mav+zc(%)	75.73	55.08	55.08	82.29	60.32
11			wa+mav+ssc(%)	71.31	54.42	54.42	78.03	55.73
12			wa+mav+mr(%)	67.37	47.54	47.54	74.91	48.85
13			wa+ssc+zc(%)	76.55	60.98	60.98	83.6	61.47
14			wa+ssc+mr(%)	72.62	55.08	55.08	77.7	54.59
15			wa+zc+mr(%)	72.62	55	55	77.7	54.59
16			wl+cd+mav(%)	79.34	60.81	60.81	76.72	64.26
17			wl+cd+ssc(%)	78.52	62.62	62.62	78.85	62.13
18			wl+cd+zc(%)	79.34	63.93	63.93	78.36	64.56
19			wl+cd+mr(%)	78.85	63.44	63.44	82.62	65.08
20			wl+mav+ssc(%)	78.52	62.13	62.13	77.86	63.6
21			wl+mav+zc(%)	81.96	67.21	67.21	80.81	70
22			wl+mav+mr(%)	80	61.63	61.63	77.21	62.62

23			wl+ssc+zc(%)	79.01	66.39	66.39	81.8	70.49
24			wl+ssc+mr(%)	79.01	63.27	63.27	82.13	64.75
25			wl+zc+mr(%)	82.13	65.4	65.4	85.57	72.13
26			cd+mav+ssc(%)	77.04	61.63	61.63	79.34	62.45
27			cd+mav+zc(%)	71.47	55.73	55.73	70	58.68
28			cd+mav+mr(%)	70.81	51.47	51.47	68.52	54.59
29			cd+ssc+zc(%)	67.21	57.04	57.04	73.11	52.78
30			cd+ssc+mr(%)	74.59	60.65	60.65	80.49	58.03
31			cd+zc+mr(%)	69.34	52.95	52.95	72.62	56.22
32			mav+ssc+zc(%)	79.67	65.24	65.24	83.27	70.98
33			mav+ssc+mr(%)	77.21	60.81	60.81	79.83	61.47
34			mav+zc+mr(%)	80.65	61.31	61.31	80.49	68.36
35			ssc+zc+mr(%)	78.85	62.13	62.13	85.08	64.75

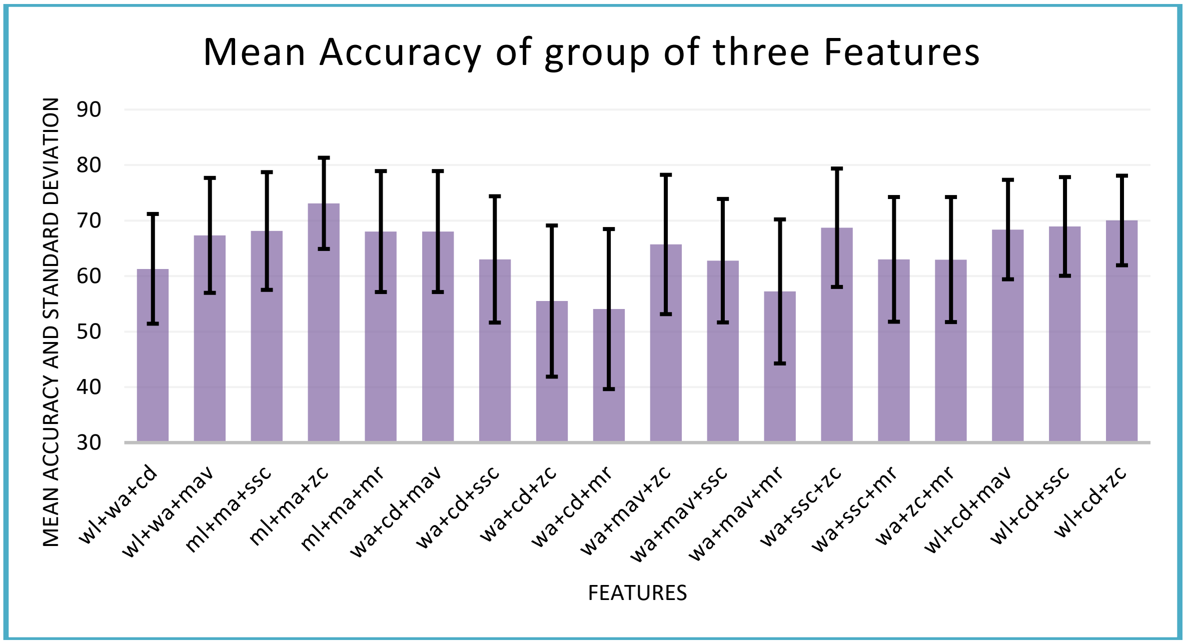

Figure 26(a): Mean Percentage accuracy of group of three features

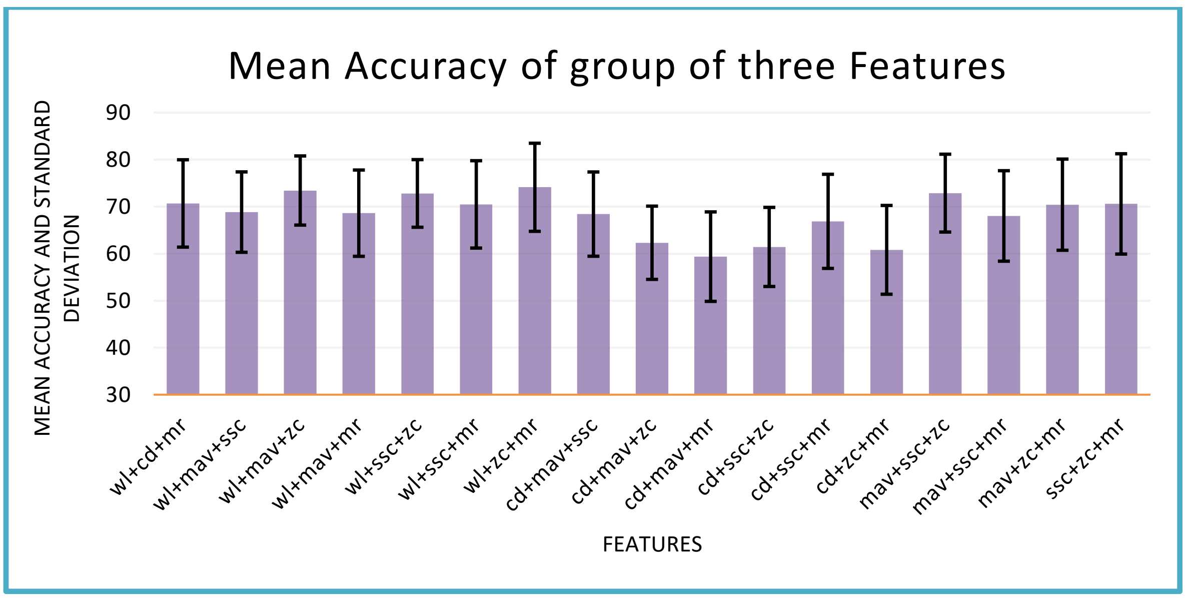

Figure 27 Mean Percentage accuracy of group of three features

4.1.4 Combination of Four Feature

Now four features are combined and decrease in the mean accuracy have been observed. Combination of CD +MAV+ SSC+ ZC gives the maximum average accuracy of 72.88 percent which is almost 1.5 percent less than group of three feature. A table has been drawn to provide the comparison of accuracies of different groups against each subject. Only groups with best mean accuracies have been discussed here.

Table 4 Percentage accuracy of group of four features

	subjects		1	2	3	4	5
No#		Percentage accuracy%					
1		wa+wl+cd+mav(%)	77.86	61.31	61.31	80.32	62.45
2		wa+wl+cd+ssc(%)	77.37	59.83	59.83	81.8	61.8
3		wa+wl+cd+zc(%)	78.52	61.14	61.14	81.14	63.44
4		wa+wl+cd+mr(%)	77.7	59.5	59.5	81.47	61.31
5		wa+wl+mav+ssc(%)	77.86	62.29	62.29	80.98	62.95
6		wa+wl+mav+zc(%)	79.18	63.27	63.27	80.32	63.6
7		wa+wl+mav+mr(%)	78.03	61.63	61.63	80.98	64.59
8		wa+wl+ssc+zc(%)	78.03	60.65	60.65	82.29	62.95
9		wa+wl+ssc+mr(%)	79.67	61.31	61.31	82.62	64.59
10		wa+wl+zc+mr(%)	79.67	61.31	61.31	82.62	64.59
11		wa+cd+mav+ssc(%)	76.88	57.37	57.37	79.5	61.31
12		wa+cd+mav+zc(%)	80.65	61.47	61.47	83.44	69.83
13		wa+cd+mav+mr(%)	70.32	51.8	51.8	79.18	54.59
14		wa+cd+ssc+zc(%)	75.4	54.42	54.42	82.13	60.98
15		wa+cd+ssc+mr(%)	68.68	46.39	46.39	75.9	49.67
16		wa+cd+zc+mr(%)	75.73	54.26	54.26	83.77	60.81
17		wa+mav+ssc+zc(%)	80	61.14	61.14	83.44	69.18

18		wa+mav+ssc+mr(%)	77.86	57.54	57.54	80.81	63.27
19		wa+mav+zc+mr(%)	80.49	62.62	62.62	84.09	69.67
20		wa+ssc+zc+mr(%)	80	57.54	57.54	84.26	64.09
21		wl+cd+mav+ssc(%)	78.68	64.75	64.75	81.31	64.59
22		wl+cd+mav+zc(%)	80.16	61.63	61.63	77.21	66.22
23		wl+cd+mav+mr(%)	80	61.63	61.63	77.21	62.62
24		wl+cd+ssc+zc(%)	77.37	65.08	65.08	82.62	67.7
25		wl+cd+ssc+mr(%)	78.19	64.75	64.75	81.31	63.27
26		wl+cd+zc+mr(%)	78.68	62.13	62.13	79.34	62.62
27		wl+mav+ssc+zc(%)	78.36	64.09	64.09	81.47	66.39
28		wl+mav+ssc+mr(%)	78.52	63.44	63.44	82.78	65.57
29		wl+mav+zc+mr(%)	79.5	61.8	61.8	81.96	67.04
30		wl+sssc+zc+mr(%)	79.67	64.75	64.75	83.44	68.03
31		cd+mav+ssc+zc(%)	79.67	65.24	65.24	83.27	70.98
32		cd+mav+ssc+mr(%)	77.21	60.81	60.81	79.83	61.47
33		cd+mav+zc+mr(%)	80.65	61.31	61.31	73.27	68.36
34		cd+ssc+zc+mr(%)	74.09	60.98	60.98	83.11	60.49
35		mav+ssc+zc+mr(%)	79.34	63.6	63.6	83.93	70

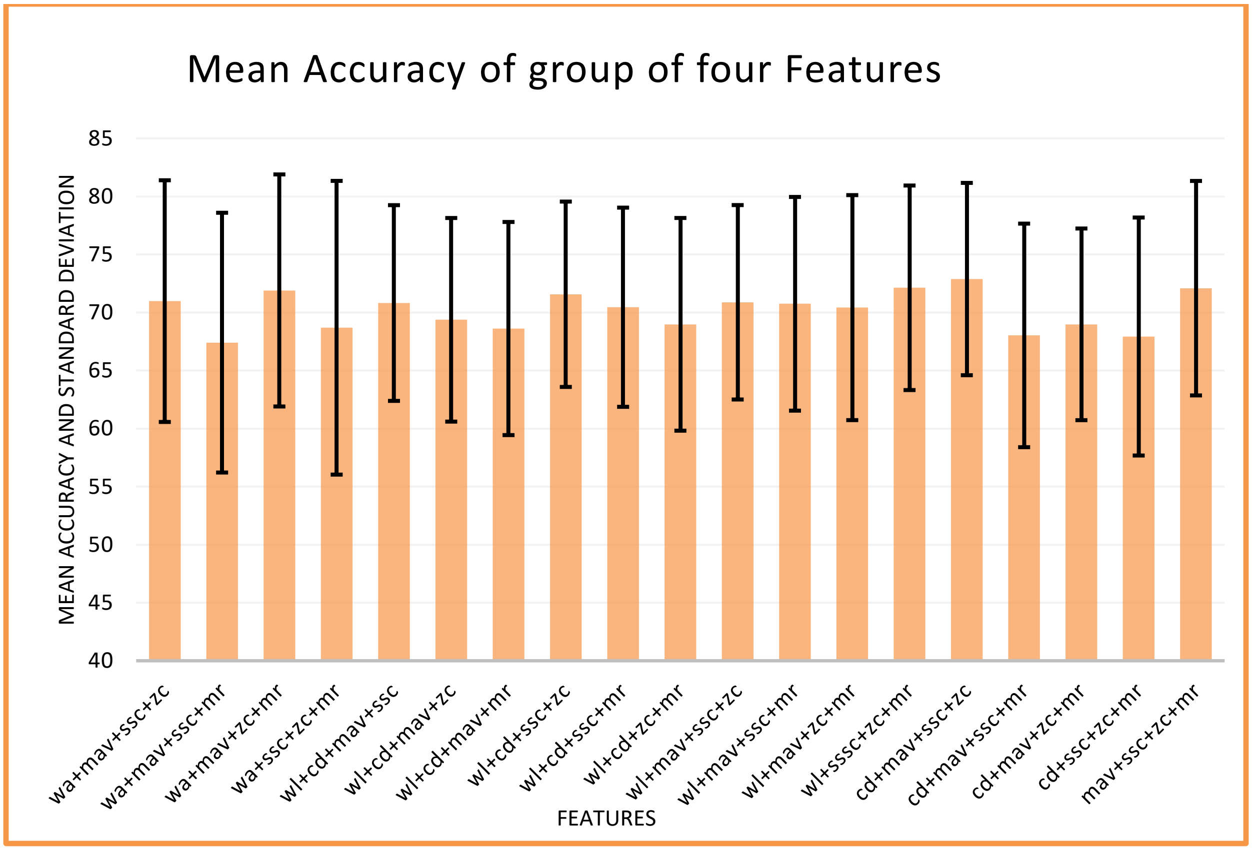

Figure 28 *Mean percentage accuracy of group of 4 features*

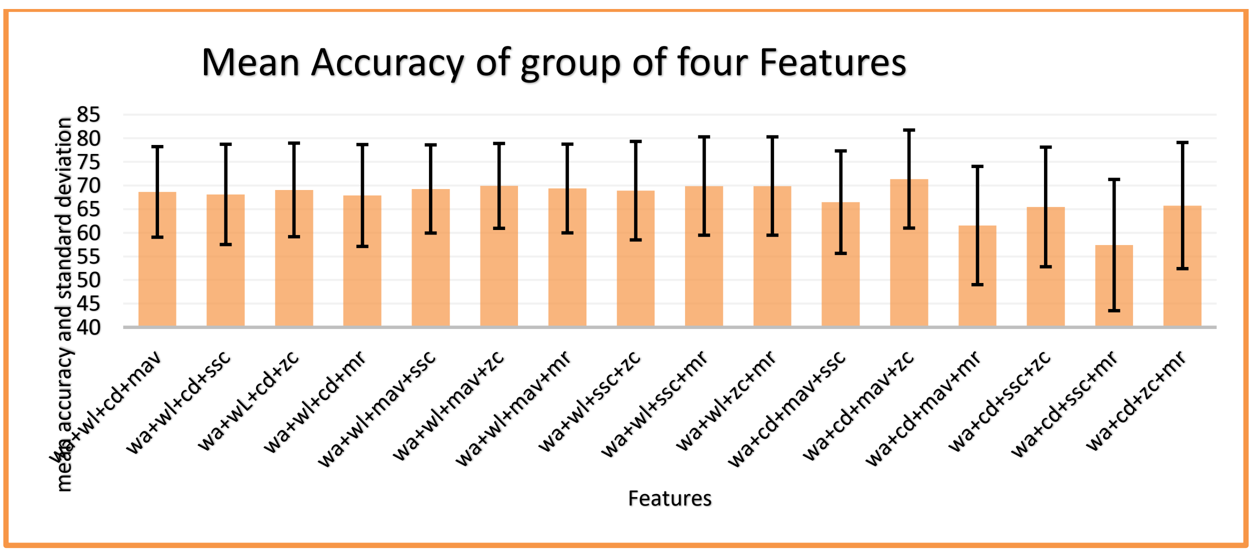

Figure 29 Mean percentage accuracy of group of 4 features

4.1.5 Combination of Five Feature

Five features are grouped, and 21 combinations are obtained. wl+cd+mav+ssc+zc gives maximum mean accuracy of 73.96 percent which is greater than group of 4 but still less than group of three features. Table below shows the comparison of groups with best average accuracy while graph in figure () shows the comparison of all 21 groups. In the graph we can notice that there is not much difference between accuracies of all groups. There is no outlier present in the graph. Accuracy of every group against each subject lies within the range difference of 15 percent.

Table 5 Percentage accuracy of group of five features

	subjects:		1	2	3	4	5
No#		Features combination	Percentage accuracy%				
1		wa+wl+cd+mav+ssc(%)	78.03	62.29	62.29	81.96	63.77
2		wa+wl+cd+mav+zc(%)	79.18	63.27	63.27	80.32	63.6
3		wa+wl+cd+mav+mr(%)	78.52	61.63	61.63	80.98	61.8
4		wa+wl+mav+zc+mr(%)	78.68	61.8	61.8	81.31	63.11
5		wa+wl+mav+ssc+zc(%)	78.85	63.27	63.27	82.62	64.42
6		wa+wl+mav+ssc+mr(%)	78.68	62.29	62.29	82.13	63.11
7		wa+wl+ssc+zc+mr(%)	78.52	61.47	61.47	82.29	64.26
8		wa+wl+cd+zc+mr(%)	78.68	58.85	58.85	82.13	63.77
9		wa+cd+mav+ssc+zc(%)	77.04	58.36	58.36	80.81	62.62
10		wa+cd+mav+ssc+mr(%)	77.54	60.49	60.49	81.47	64.09
11		wa+cd+mav+zc+mr(%)	72.45	57.21	57.21	81.14	56.88
12		wa+cd+ssc+zc+mr(%)	76.06	58.68	58.68	81.31	58.85
13		wa+wl+cd+ssc+zc(%)	78.03	61.96	61.96	82.95	64.59
14		wa+wl+cd+ssc+mr(%)	78.52	61.8	61.8	82.13	63.11
15		wa+mav+ssc+zc+mr(%)	78.03	59.83	59.83	81.8	65.4
16		wl+cd+mav+ssc+zc(%)	80.81	67.04	67.04	83.6	71.14
17		wl+cd+mav+ssc+mr(%)	78.36	63.27	63.27	81.14	63.93
18		wl+cd+mav+zc+mr(%)	81.14	66.55	66.55	81.63	69.5

19		wl+mav+ssc+zc+mr(%)	79.83	67.21	67.21	83.44	71.31
20		wl+cd+zc+ssc+mr(%)	79.83	66.88	66.88	85.4	70.81
21		cd+mav+ssc+zc+mr(%)	79.34	63.6	63.6	83.93	70

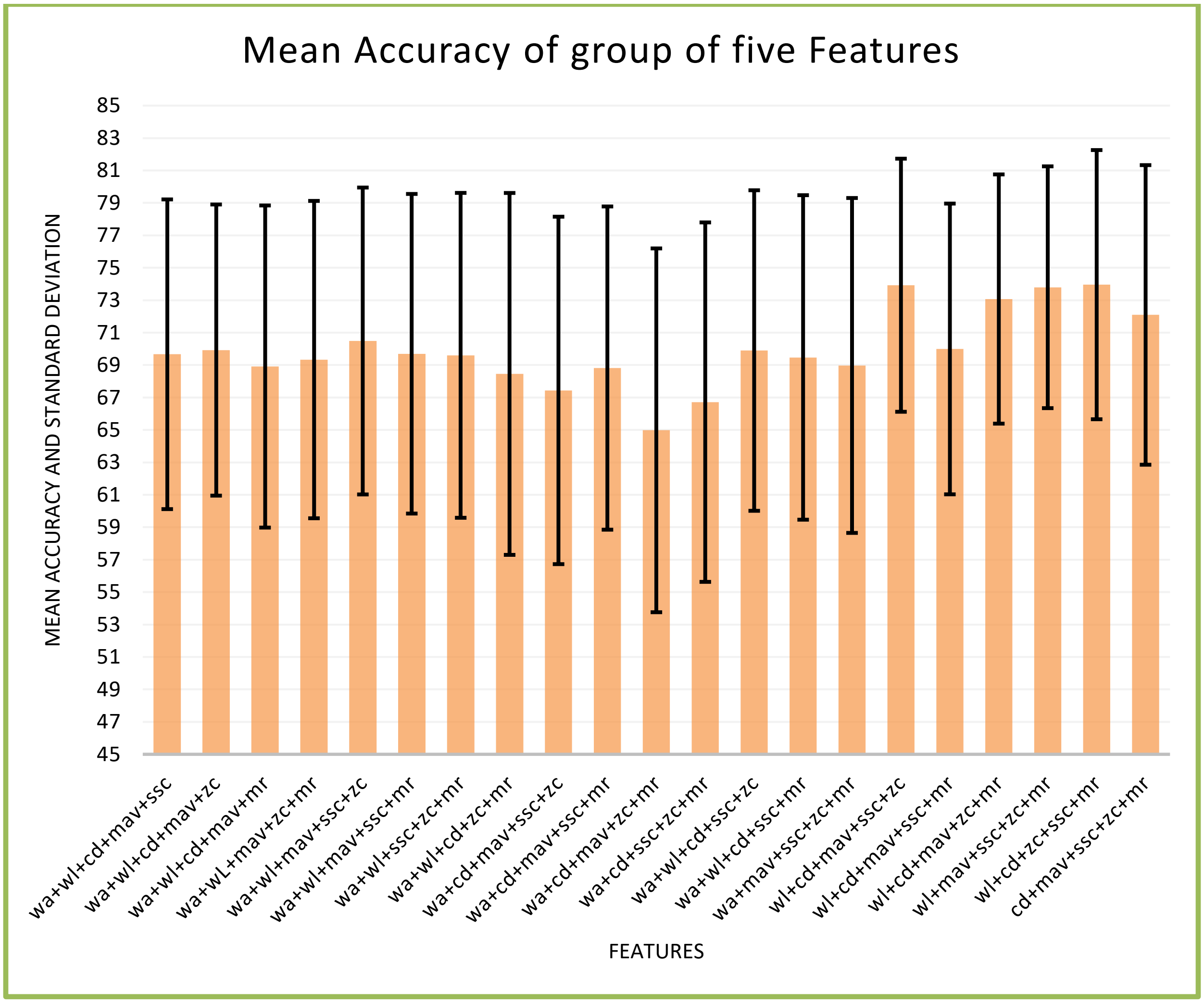

Figure 30: Mean percentage accuracy of group of 5 features

4.1.6 Combination of Six Feature

In the end six features are grouped to obtain seven groups and their accuracies are compared. 73.896 is the maximum average accuracy obtained from the group of WI+CD+MAV+SSC+ZC+MR. There is a decrease in accuracy as compared to the group of five or three features while increase in accuracy as compared to the group of two or four features.

Table 6 Percentage mean accuracy of group of six features

	subject		1	2	3	4	5
No#		Features combination	Percentage accuracy%				
1		wa+wl+cd+mav+ssc+zc(%)	80.16	65.57	65.57	84.59	70.65
2		wa+wl+cd+mav+ssc+mr(%)	78.68	62.29	62.29	82.13	63.11
3		wa+cd+mav+ssc+zc+mr(%)	79.01	63.11	63.11	83.6	68.85
4		wa+wl+mav+ssc+zc+mr(%)	80	65.08	65.08	84.09	69.18
5		wa+wl+cd+mav+zc+mr(%)	80.98	65.08	65.08	83.44	68.85
6		wl+cd+mav+ssc+zc+mr(%)	80.49	66.55	66.55	84.42	71.47
7		wa+wl+cd+ssc+zc+mr(%)	78.19	64.91	64.91	84.59	68.85

Graphs shows the comparison of seven groups against 5 subjects. Graph shows the maximum difference between accuracy of any group against single subject is less than 10 percent. Overall minimum accuracy has been improved.

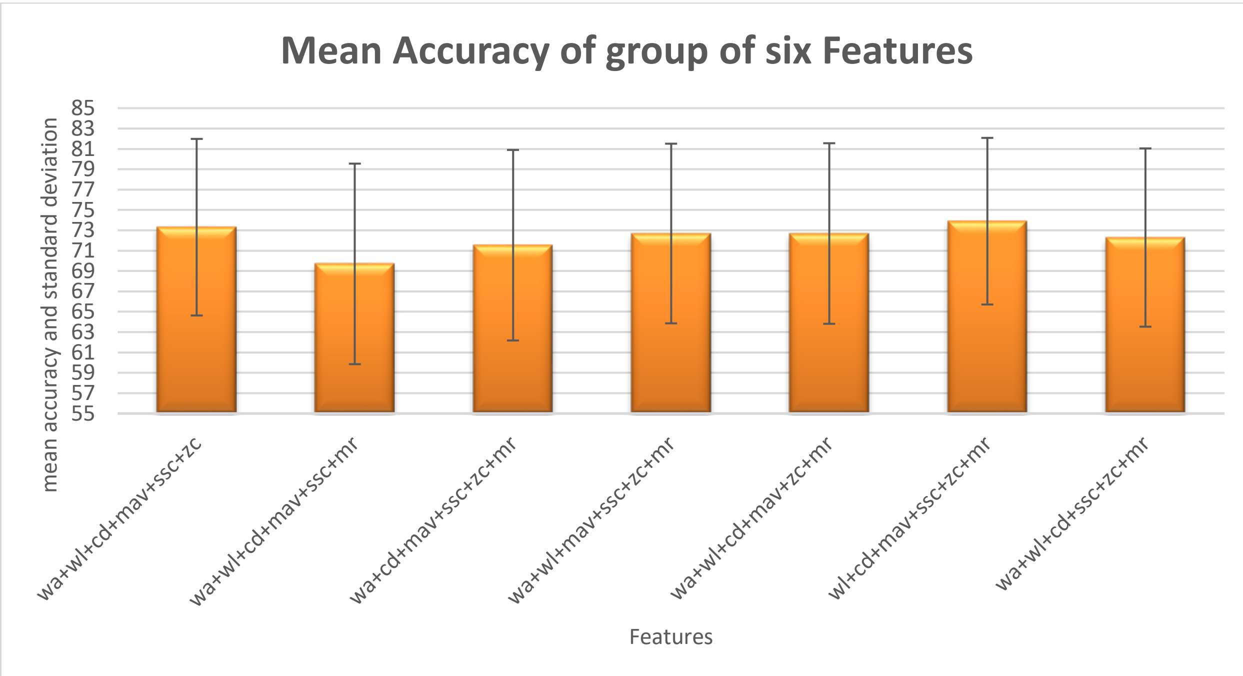

Figure 31: Mean percentage accuracy of group of six features

4.1.7 Combination of Seven Feature

Seven features together provide an average efficiency of 73.044 which is better than two or four features together. A graph has been plotted between subject versus accuracy in figure.

Table 7 Percentage accuracy of group of seven features

wa+wl+cd+mav+ssc+zc+mr(%)		
subject:		Percentage accuracy%
1		80.49
2		64.91
3		64.91
4		84.91
5		70

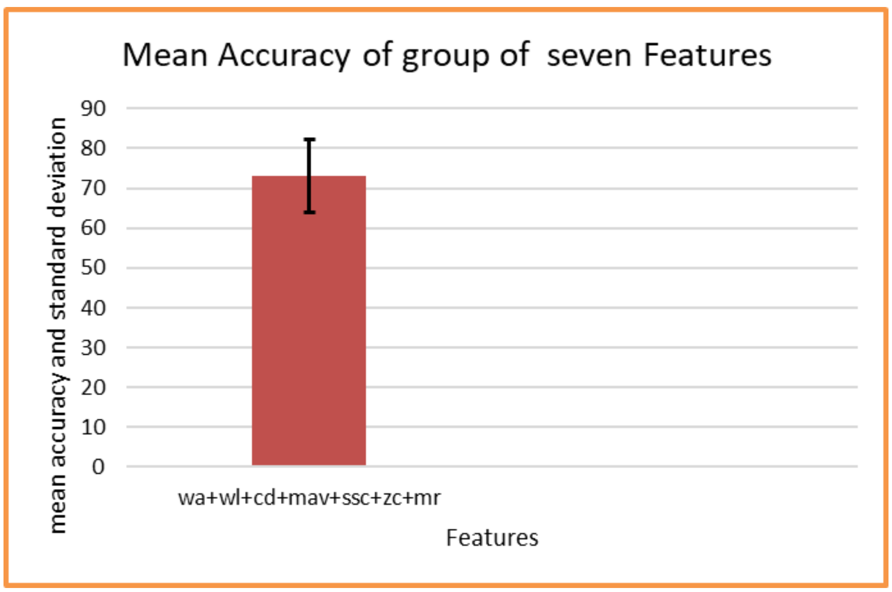

Figure 32: Mean percentage accuracy of group of 7 features

4.2 STASISTICAL ANALYSIS (ANOVA TEST)

To know if the results are statistically significant or not one-way anova test is performed between the groups and within the groups. There is significant difference in mean of each group combinations. anova is performed on each subject and mean of different features combinations is analyzed and prove significant. Anova compare variance between and within the groups.it analyses if mean of two or more groups is equal or different due to some random error or its statistically different. Anova assume normal distributions. P value is a probability. Higher p value results are not significant. 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. If the p value is lower than 0.05 than there is significant difference in mean of subjects otherwise not.

4.2.1 Subject: One (ANOVA)

p = 0.05

α =5%

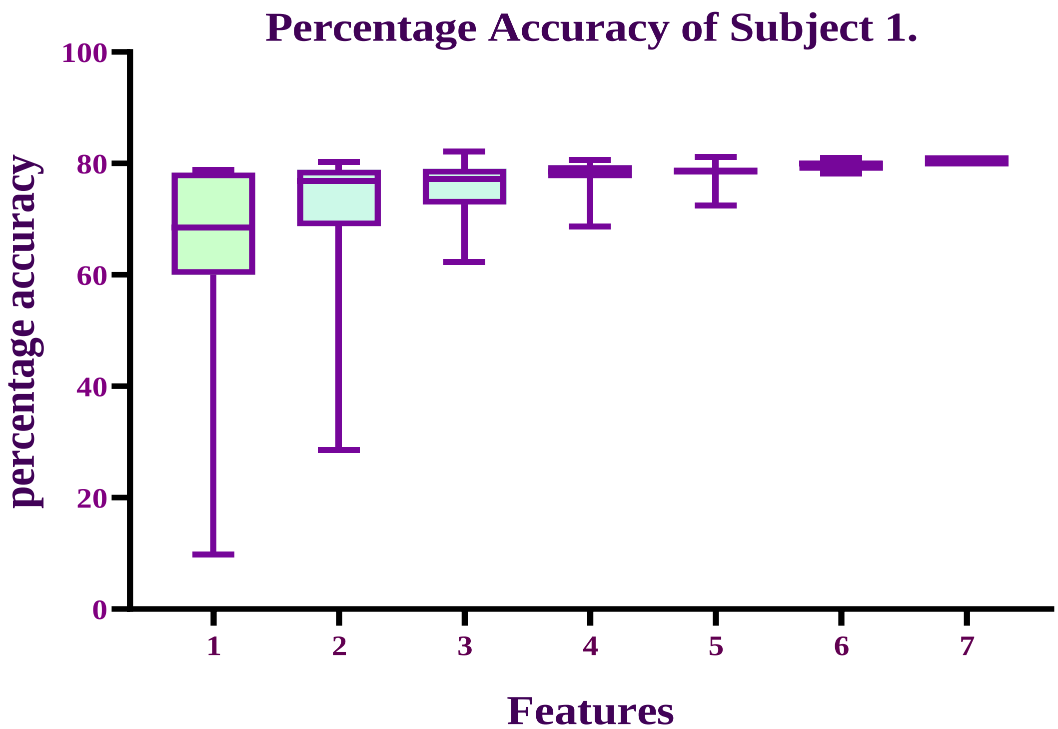

Figure 33: % accuracy of subject 1 (one-way ANOVA)

Table 8 Anova results for subject 1

ANOVA RESULTS	
F value	**5.399**
P value	**<0.0001**
Significant diff. among means (P < 0.05)	**Yes**
R squared	**0.2126**

4.2.2 Subject: Two (ANOVA)

p = 0.05

α =5%

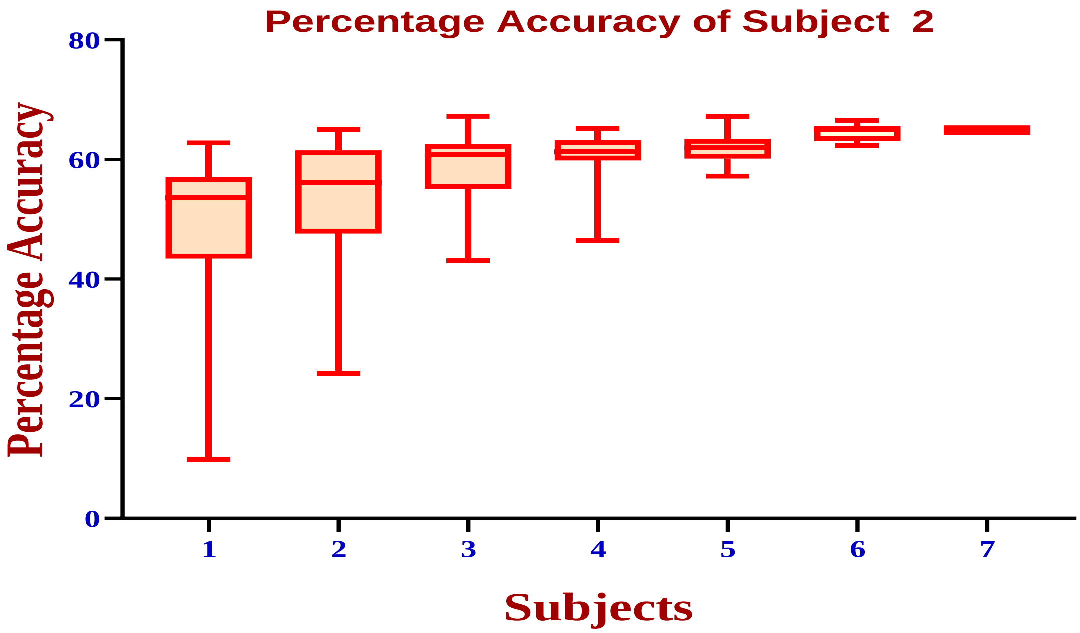

Figure 34: % accuracy of subject 2(one-way ANOVA)

ANOVA RESULTS	
F value	**7.494**
P value	**<0.0001**
Significant diff. among means (P < 0.05)	**Yes**
R squared	**0.2726**

Table 9: Anova results for subject 2

4.2.3 Subject: Three (ANOVA)

p = 0.05

α =5%

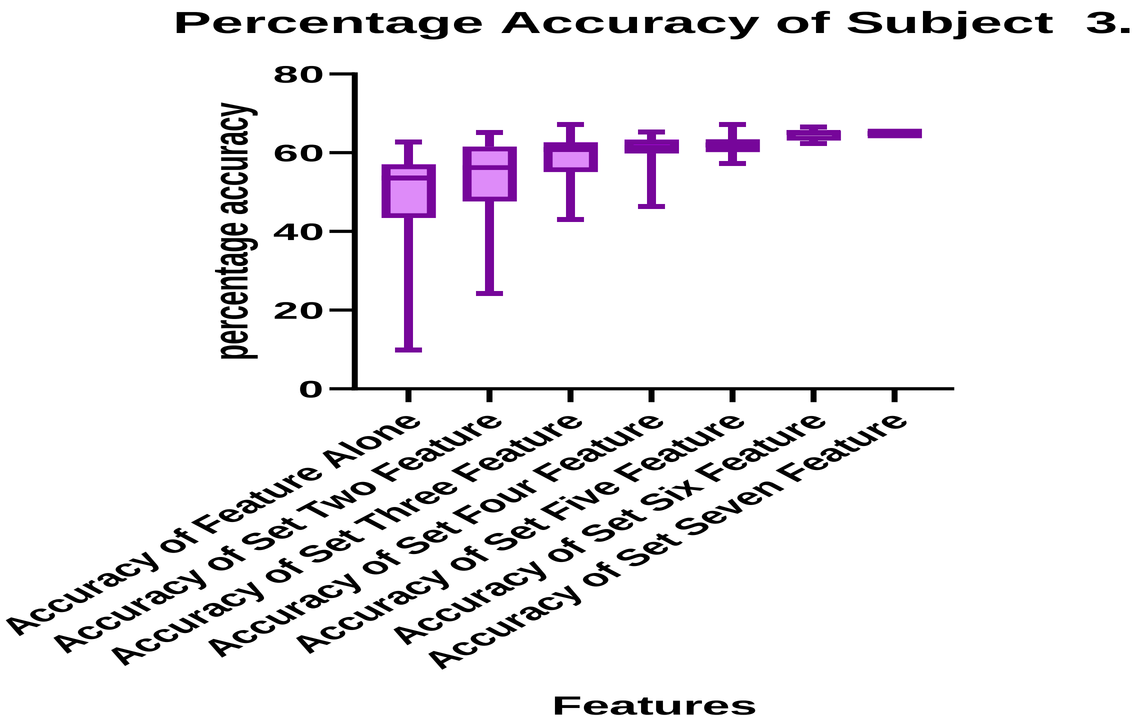

Figure 35: % accuracy of subject 3(one-way ANOVA)

ANOVA RESULTS	
F value	**7.494**
P value	**<0.0001**
Significant diff. among means (P < 0.05)	**Yes**
R squared	**0.2726**

Table 10: Anova results for subject 3

4.2.4 Subject: Four (ANOVA)

p = 0.05

α =5%

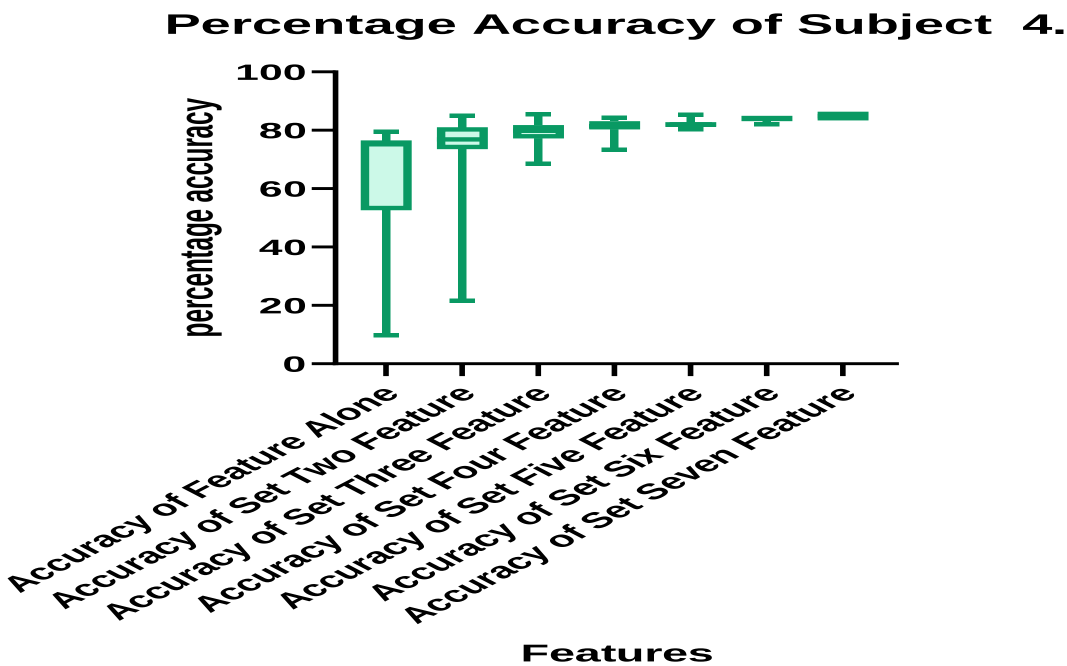

Figure 36: % accuracy of subject 4(one-way ANOVA)

ANOVA RESULTS	
F value	6.850
P value	<0.0001
Significant diff. among means (P < 0.05)	Yes
R squared	0.2551

Table 11: Anova results for subject 4

4.2.5 Subject: Five (ANOVA)

p = 0.05

α =5%

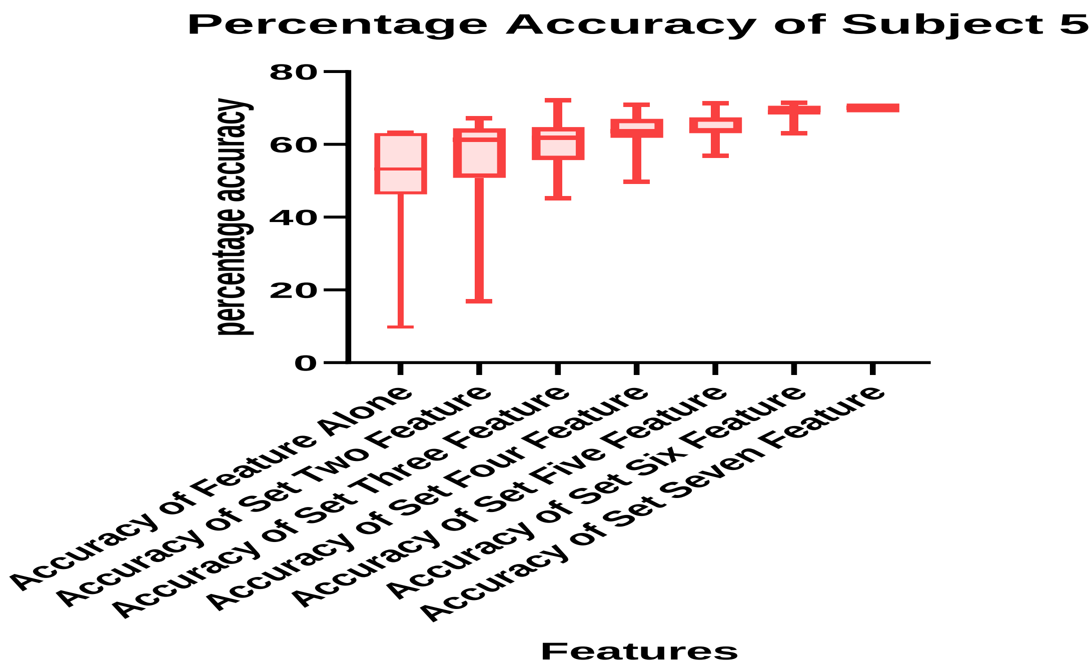

Figure 37: % accuracy of subject 5(one-way ANOVA)

ANOVA RESULTS	
F value	**6.579**
P value	**<0.0001**
Significant diff. among means ($P < 0.05$)	**Yes**
R squared	**0.2526**

Table 12: Anova results for subject 5

CHAPTER 5: CONCLUSION

As study is conducted to improve pattern recognition and improving technique for s-emg signal processing. The comparison between features combinations will help researchers to estimate the better classifier for the analysis of s-emg signals.it is concluded by the experiment that maximum accuracy is gain by combining of 3 feature together if we add more features accuracy decreases same as with the less number of features than 3.

Accuracies of features are compared individually as well as grouped in the groups of 2, 3,6. Maximum average mean accuracies of all the combinations are compared in the table given below:

Table 13: Comparison of maximum mean accuracies of different groups of features

Groups:	**Max. Mean accuracy**
Individual feature	**68.88**
Group of two features	**70.782**
Group of three features	**74.126**
Group of four features	**72.88**
Group of five features	**73.96**
Group of six features	**73.89**
Seven features together	**73.04**

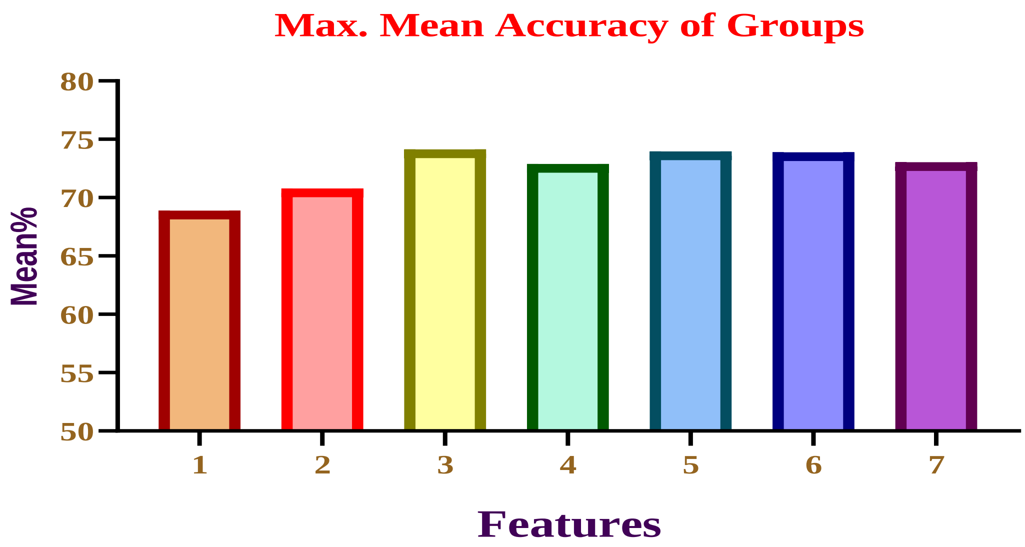

Figure 38: Graph between maximum mean accuracy and different 7 group of features

It is concluded that combinations of feature give better results until number of features increases more than 3. It is also deduced that as number of features in a combination increases computational time also increases which is not a good sign it causes delay in output signal. It can be seen in the table that the maximum average accuracy is obtained from the group of three features together. Maximum mean frequency increases from one feature to three features then decreases for four features and again increases at five features and then decreases for six and seven features together. While group of three features provides overall best results

CHAPTER 6: FUTURE WORK

Many factors are required to be analysis to noise-free signal acquisition, compatible sensitized system and robust control algorithms.

recording and controlling of various gestures and grasping; as well capacity to detect/perceive various sensation such as pressure, force, temperature, stiffness, vibration etc of human body. And analyze these signals.

analyzing signal of different hand movements. Pattern recognition by application of other machine learning technique having less computational time than LDA. In this research only time domain features are computed while time frequency domain and frequency domain features still need to be analyze in future. Different combinations in features can give better pattern recognition if analyzed in coming days. These combinations can be further analyzed with different movements finger hand or arms.

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