EMG Feature Reduction Technique For Optimal Accuracies

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ABSTRACT

The recording of electrical activity which is produced by muscles is known as an Electromyogram or Electromyographic (EMG) signal. The generation of electric current during the contraction of muscles is measured by it. The insight of muscles dynamics and neural activation is provided by EMG signal and is thus significant for several different applications, such as the studies that try to identify deficiencies of neuromuscular. For researchers and practitioners, signal of EMG is very important to observe and evaluate the muscles condition and the outcome of the rehabilitation training. The signal of EMG features precision and factors vary correspondingly with signal of muscle, fatigue, and features.

The hand movements classification based on signals of surface electromyography (sEMG) is a key problem in assistive devices and rehabilitation system control. The classification of movements of hand from sEMG is a method that has different applications like rehabilitation, interaction of human-machine and prosthetic control. The main issue is that by using increase number of features and channels of EMG in order to maximize the number of control commands can produce a feature vector of high dimensional. The major challenge is the process development to predict the current motion robustly and accurately based on incoming sEMG data. To overcome the problems of accuracy and computation linked with high dimension vector, feature reduction technique is applied that converts the data to low dimension vector space with a bit loss of valuable informative data.

The aim of this thesis is to extract features and to reduce its dimensionality using PCA to improve classification success rate and compare the findings of classification accuracy before and after applied PCA technique. Six different classifiers were used on the EMG data before and after using feature reduction technique and a comparative study of finding is presented in this thesis study.

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CHAPTER 1: INTRODUCTION

Among the most valuable electrophysiological signals are electromyography (EMG) signals which are commonly used in applications of medical and engineering [1]. It is used in various applications of rehabilitation and human-computer interface (HCI) by generating different commands for these applications in the framework of engineering. EMG signals classification based control systems are generally recognized as Myoelectric Control Systems (MCSs) [2]. The two among many of the main likely applications of MCSs are electric powered wheelchairs [4] and powered upper-limb prostheses [3]. The user's movements recognized by relating predetermined threshold with magnitude features of EMG signals are the most commercial EMG based prostheses [5]. But these classifications can only produces control commands in small numbers, like scheme of open and close with only an impetus speed.

The EMG prostheses of multifunction have been established in a number of ways since the early 1990s [6 – 10]. In order to maximize the efficacy of these multipurpose EMG prostheses, research groups mostly increases the amount of recognized activities that can directly increase the control commands in numbers. Conversely, the need of increased informative data to be extracted from the signal of EMG leads to it. The information resulting from the recognition systems of EMG can be increased by using two most important ways. One is to utilize the data that exists in the signal features and other is to obtain information from different positions of a muscle [3]. However, a feature vector of high dimension yields simultaneously by maximizing the total of EMG features and EMG channels which also produces the dimensionality problem curse [6]. It is therefore required to adopt an effective technique of dimensionality reduction [8 – 17] to produce an effective outcome in all associated costs, i.e., performance of classification, computation, measurement, and in storage.

The frequent way of reduction of dimensionality of the EMG feature vector is feature projection [2]. Numerous studies have proved that projection of feature is preferable in performance than other techniques of reduction of dimensionality including Euclidean distance used in selection of features [8]. In feature projection, a suitable subclass of new features from a set of original feature is created where the criteria of learning is optimized. By using this method, not only the classifier power increases but also reduces the feature vector dimensions [8 – 17]. Feature vector extraction by Englehart et al. [8] is done over a Wavelet Packet Transform (WPT) and a Discrete Wavelet Transform (DWT). They used an unsupervised linear method known as Principle Component Analysis (PCA) for dimensionality reduction. Numerous latest researches have engaged PCA as the method of reduction of feature in different applications of EMG [9 – 12]. Another technique of linking PCA and a Self-Organizing Feature Map (SOFM) was employed by Chu et al. [13] which is a method of unsupervised linear-nonlinear. However, the classifier ability is decreased by the dimensionality reduction if dimension reduced by PCA is fewer than twenty orders [14].

Linear Discriminant Analysis (LDA) is the supervised linear method and performance wise competitive with Nonlinear Discriminant Analysis (NLDA) concerning to class separability [15]. Also, comparative to PCA and SOFM, LDA has better performance of classification. In addition, from the processing time point of view, it is far more proficient than NLDA and SOFM. Furthermore, some other simple methods of extraction in the domain of time and frequency [20 – 21] like autoregressive coefficients, energy, mean power frequency, mean absolute value, variance, zero crossing rate, and median power frequency can be arrayed as method of reduction of feature [22 – 23].

This study estimate the act of feature projection methods suggested by using a simple systems of pattern recognition established on classifier of one linear discriminant (LD) and different EMG sets of feature which represents both approaches, i.e., time domain and time scale. In this study, the main focus is on extraction of features and feature reduction techniques specifically for solving problem of hand gesture classification with an importance of practical considerations. Figure - 1 represents a general procedure of a recognition system of a hand motion which is shown below.

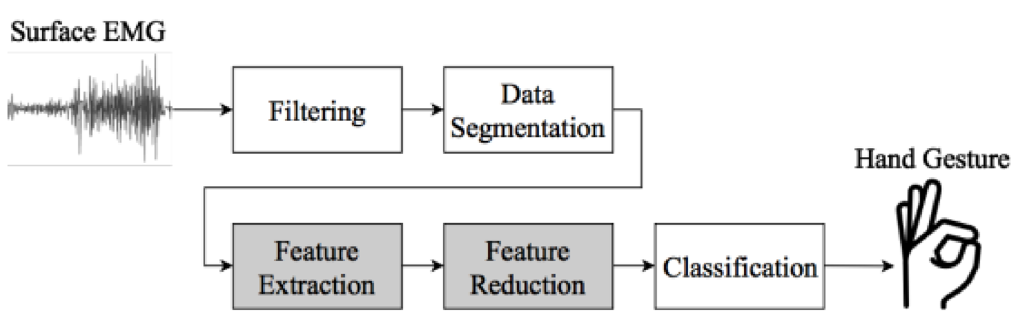

Figure 1 : A common method of a recognition system of hand motion.

Several studies came to be on movement identification of ordinary human limbed using signals by surface EMG which is to be used for control of prosthetic arm as an input since the 1980's. A non-invasive method have used to record an EMG signal of the forearm [24] and upper arm [25] in these studies which demonstrates the significance of these researches for the purpose to ease such problems of an individuals to have a better life. Below is given the short background of the EMG signal. The aim and objective is also discussed. And, the thesis structure is outlined at last of this chapter.

1.1 EMG Background

Among most important works in the studies of nerve conduction is electromyography (EMG). It is a part of the methods for assessing the action potential that is detected, recorded and produced by the body muscles. A diagnostic procedure for the control of motor neurons and health assessment of the muscle is also known as EMG. The central nervous system (CNS) generates the pulse and hence it is the origin of EMG action potential.

The movement of body parts of a person is done through the signals send from the brain. These signals controlled muscle fibers through the motor neuron which results in contraction and relaxation of a muscle. The transferred brain signals carrying information through the motor neurons and along the nerves moves in pulse repetition, also to be called by means of frequency. The produced action potentials as of this instance are recognized as Motor Unit Action Potentials (MUAPs) [26].

The summation of the amplitudes generated is EMG or known as MUAPs. The activation of numeral motor unit and the firing rate of an individual motor unit increases directly proportional to the contraction of voluntary muscle of the individual. The physiological operation understanding makes easy by EMG that gives the information about force generated by muscle, movement, and functions. The countless activities can be done by the EMG signals generation that allows us to interact with the world. De Luca (1977) extensively discussed the properties and use of EMG [27].

1.2 Aims and Objectives

The aim of this thesis is to develop the EMG feature reduction technique for optimal accuracies. The most important objective of this thesis is to use different feature reduction techniques and choose the best one that can reduce space use by the raw data and work fast without removing any useful information.

1.3 Structure of Thesis

This study is organized round the chief objective of EMG feature reduction techniques for optimal accuracies. The study starts with an introductory Chapter 1; Chapter 2 presents associated work in this study area. Chapter 3 describes different methods. Chapter 4 summarizes, examines and discusses results. Chapter 5 is related to Suggestions for future work.

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CHAPTER 2: REVIEW OF A LITERATURE

This chapter is related to the essential background knowledge and literature that is relevant for understanding the work covered in later chapters of the thesis. The main topics discussed here are the Electromyography (EMG) signals basics and its characteristics.

2.1 Physiology of the Electromyography (EMG) Signal

Among other methods of recording, one method of recording electrophysiological signals is Electromyography (EMG). Several people are possibly aware of with other recording methods of electrophysiological signals which includes Electroencephalography (EEG), the electrical activity recording occurs along the scalp, and Electrocardiography (ECG, or EKG), the recording of heart the electrical activity, etc. Same like that EMG is a method or procedure to compute the activity of electrical signal produced by the skeletal muscle fibers when they contract. Muscle fibers are like a long tubular cell and a bundle of muscle fibers formed a muscle. The composition of EMG signal is like that the signals from each cell of a muscle superpose each other and modified by a physiology of person. The device used to record EMG is called Electromyography, and the recorded waveform is known as Electromyogram, or the Electromyography signal (in short, the EMG).

The source of electrical for reading the EMG signal is basically the membrane potential change of a muscle or we can say the voltage difference from ionic current flows across the muscle cells membranes when activated electrically or neurologically which causes contraction of a muscle and related measure of potassium ions (K+) and calcium ions (Ca++) [28]. As a result of the EMG signal, a valuable analysis of the resulting electrical activity caused by underlying biological processes of muscles can be analyzed.

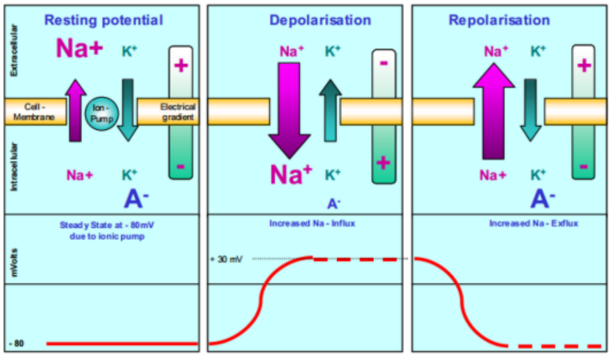
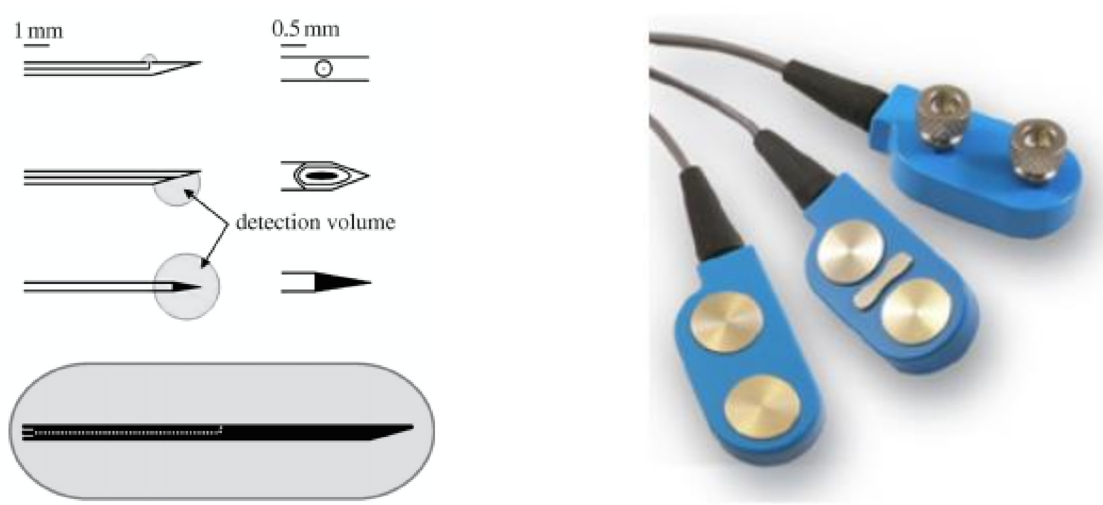


Figure 2 : The Illustration of EMG signal formation

Furthermore, one can deduce the neural movement of the spinal cord and possibly the central nervous system. The biomechanics of human or animal movement, the deficiencies of neuromuscular like affected by stroke and Parkinson's disease [30] can be diagnosed by analyzing EMG signal. The signal of EMG relative to a potential change of muscle cell membrane is illustrated in Figure 2 which gives a rough estimate of the observed changes in electrical potential just as observed by an electrode and caused by the movement of ions of sodium and ions of potassium through sheaths of a cell (by active transport). Muscle fiber membrane resting potential is approximately equal to -80/-90 mV [28, 29] relative to external side of cell when it is not contracted. Ion pumps maintained this variance which offers the active transport as shown in Figure 1. The action is controlled along the nerve motor when anterior horn cell of alpha-motor is stimulated by the central nervous system or by a reflex and leading to a formed electrical potential at the motor end plates which basically changes in muscle fiber membrane diffusion characteristics, primary the inflow of sodium ions. Therefore, the membrane develops depolarization that is speedily inverted leading to repolarization through the ion pumps.

The acquisition methods for EMG signals are categorized into two types: invasive (also known as intramuscular) and non-invasive. This thesis focuses on the method of non-invasive which is also known as Surface Electromyography (sEMG). Both methods are categorized on the basis of electrodes being used (see below figure).



(a) Typical intramuscular electrodes schematics [35] (b) Surface electrodes picture from Motion lab Systems [36]

Figure 3: Electrodes for iEMG and sEMG

The non-invasive method contrary to other method is also usually a preferable method where possible as it is comparatively free of distress and offers a considerable lesser infection risk [32, 33]. Surface EMG (sEMG for short) acquisition a non-intrusive, relatively simple approach and is normally achieved by placing a electrodes pair or an array of more complex multiple electrodes on the surface of skin above the muscle to record the electrical activity. On the other hand, intramuscular EMG (iEMG) allow placement of monopolar needle or concentric needle electrodes near to particular muscles tissue of concern but are less useful for general usages. Intramuscular EMG signals are less noisy recording and much more selective as sEMG signal is influenced by the tissue that is under skin depth at the recording site [33].

2.1.1 Generic Physiology Electromyography (EMG) Signal

A paper reviewed on the decomposition of EMG signal written by Stashuk's [33] gives a very good description about the generation of EMG signal. The discussion in that paper is followed by following material.

2.1.1.1 Muscle Fiber Action Potential (MFAP)

Fibers of a muscle are basically the casual term for cells of a muscle, or myocytes, which are the singular components combined to make skeletal muscles. Skeletal muscles are responsible for making posture, creating motion and changes in position of a body. Their size and shape depends on the location of the muscle in a body, but overall structure remains the same across people.

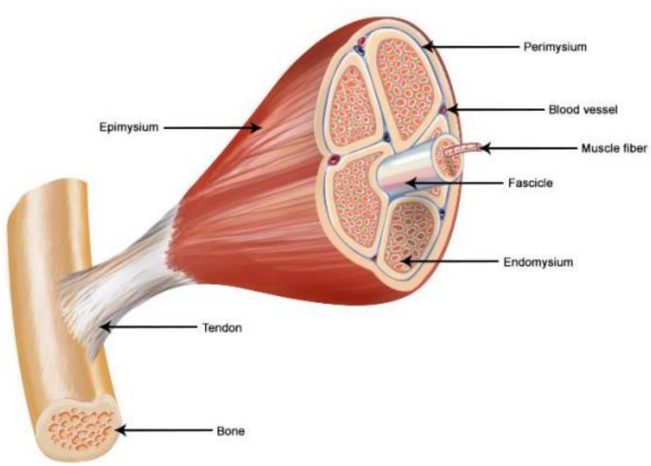


Figure 4: Structure of Skeletal Muscle (National Cancer Institute)

Skeletal muscles are usually divided into string like fascicles which are bundled in parallel. These strings like structures are further divided into even smaller multinucleated cells which are known as muscle fibers. The above figure shows the structure of a skeletal muscle. Two types of muscle fibers are there namely as type I muscle fibers and type II muscle fibers. Muscle fibers of both types are classified based on the speed of contraction of the fiber. Slow-twitch muscle fibers are known as type I which needs more time in order to achieve their maximum tension while fast-twitch muscle fibers are known as type II and needs less time in order to achieve their maximum tension. Muscle fibers usually have a 50 – 100 µm diameter, and 2 – 6 cm length [34]. Every single muscle fiber is typically excited in only single place by only single motor neuron, normally close to its midpoint [34]. The structure, known as neuromuscular junction transmits motor neurons to muscle fiber. Action potentials (AP) generated by the excited muscle fiber propagates away from the neuromuscular junction and is relatively slow (3 – 5 m/s) in both direction which is same like the transmission of action potentials alongside the neuron axons. This action potential is the important element contributing to the EMG signal detected and is known as a muscle fiber action potential (MFAP). The diameter of the fiber, type of electrodes and their configuration, its position comparative to the recognition site, and the velocity conduction will influence the characteristics of MFAPs.

2.1.1.2 Motor Unit Action Potential (MUAP)

The muscle fibers are controlled together in a group and are not excited individually. This controlled group of muscle fibers is known as motor unit. A single motor neuron made up a motor unit and its corresponding skeletal muscle fibers. A muscle is managed typically by large motor neurons nearly around 100 [34]. A motor unit can stimulate anyplace from 100 to 1000 scattered fibers of muscle over a significant portion of the muscle. Each action potential of the motor neuron gets truly and synchronously response from all of the muscle fibers stimulated by the similar motor neuron [34]. Normally, as a result, each MFAP are normally not sensed but all motor units' MFAPs summation is sensed. This summation of spatial and temporal of every action potential within a motor unit is called as a motor unit action potential (MUAP). The cumulative sum of the each MUAP is measured at the surface of skin as a signal. The factors on which the detected number of MUAPs depends on the electrode placement as well as the electrodes surface area. Moreover, overlapping may occur on muscle fibers from different motor units which upsurges detected number of MUAPs at surface of the skin. The MUAPs cannot be distinguished at the skin's surface without further processing as they are grouped together.

Let $MFAP_i$ (t) be the waveform generated by i-th fiber of a motor unit of a muscle fiber action potential. And, let $MUAP_j$ (t) be the motor unit of j-th fiber electrical potential rises as a summation of entire MFAPs:

$$\mathrm{MUAP}_j(t) = \sum_{i=1}^{N_j} \mathrm{MFAP}_i(t - \tau_i) S_i \qquad (2.1.1.1)$$

Where,

τ_i = Temporal offset of $MFAP_i$ (t).

N_j = Number of fibers in "j" motor unit.

S_i = Represents the function of neuromuscular junction by a binary number. It has a value of 0 if fiber is not fired and 1 if fired.

The muscle fiber velocity conduction and the neuromuscular junction location are the factors on which τ_i depends. As pointed out before, the motor unit size is represented by N_j and is approximately equal to 100 – 1000. An electrical signal generated by the sum of resulting current which is produced when, in synchrony, hundreds of muscle fibers activated by an individual action potential in a motor neuron is freely measurable exterior to the muscle itself [34]. The diameter and location of the few closest muscle fibers influences the MUAP size in practice as of the reduction of MFAP with a space to the sensing electrode.

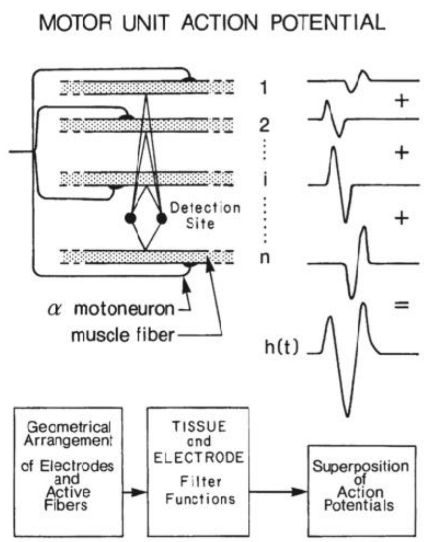


Figure 5 : An illustration of MUAP composition

The MUAP composition as individual MFAPs summation is shown in figure 5. The waveforms of MUAP will differ in shape generally because of the variations in fiber potentials delay (affecting τ_i), possible electrode position changes relative to fibers of the muscle distressing MFAP$_i$), and the risk of failing of a specific fiber to fire (affecting S_i). The stochastic biological variability source is these variations in the waveform of MUAP [33].

2.1.1.3 Motor Unit Action Potential Train (MUAPT)

It is necessary to fire an action potentials temporal sequence by the specific motor neuron in order to keep or exert more force produced by a muscle. This fired temporal sequence of action potentials is known as spike train. One MUAP is generated by a single motor neuron action potential as already discussed in last section. Motor Unit Action Potential Train (MUAPT) is a MUAPs temporal arrangement which resulted when spike train arrived at the junctions of neuromuscular of motor unit of all fibers of a muscle [33].

$$\mathrm{MUAPT}_j(t) = \sum_{k=1}^{M_j} \mathrm{MUAP}_{jk}\left(t - \delta_{jk}\right) \qquad (2.1.1.2)$$

Where,

$\mathrm{MUAPT}_j(\mathrm{t}) =$ MUAPT of the *j*-th motor unit.

$\mathrm{MUAP}_{jk}(\mathrm{t}) =$ MUAP generated during the firing (k-th) of the *j*-th motor unit.

M_j = Number of times the *j*-th motor unit fires.

δ_{jk} = Firing time (k-th) of the *j*-th motor unit.

2.1.1.4 Composite EMG Signal

An asynchronous barrage of action potentials generated by many motor neurons when there is a greater force required than minimum. Because of the superposition property of electric fields, an electrode placed on the surface of skin or either injected into a muscle measures the MUAPTs spatial and temporal summation backed from entire motor units recruited inside the “sphere of listening”. The electric potentials complex pattern resulted is known as composite EMG signal and it is usually in the order of 100μV in amplitude [34]. As the force of muscle increases, usually more motor units are enlisted. At poles apart, distinct motor units are enlisted and remain lively for different time spans. Every single MUAPT has its personal features of firing intervals in addition and within every MUAPT, the interval of firing changes too. The decomposition of the detected EMG signal from different motor units into its MUAPTs is a general direction of research. Normally, on the iEMG signal, decomposition of EMG is performed as few MUAPTs measured by iEMG. On the other hand, sEMG makes decomposition very difficult as it detects many more MUAPTs.

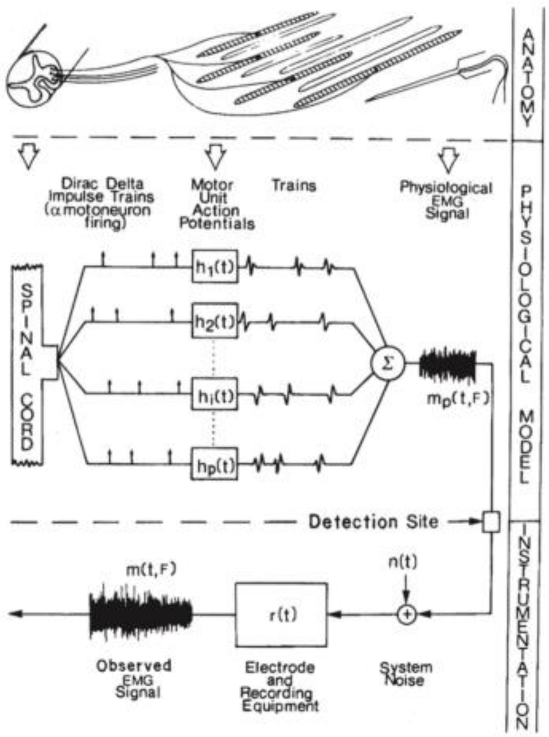


Figure 6 : Mathematical and physiological model for the detected EMG signal composition (from Stashuk [33])

EMG signal representation using both physiological and anatomical model is shown in Figure 6.

$$\mathrm{EMG}(t) = \sum_{j=1}^{N_m} \mathrm{MUAPT}_j(t) + n(t) \tag{2.1.1.3}$$

Where,

$\mathrm{MUAPT}_j(\mathrm{t})$ = MUAPT of the j-th motor unit.

$n(\mathrm{t})$ = Backgorund noise of instrumentation.

N_m = Number of motor units that are active.

δ_{jk} = Firing time (k-th) of the j-th motor unit.

Figure 7 which is shown below demonstrates from Nawab's paper, the example of decomposition result on the iEMG signal [37].

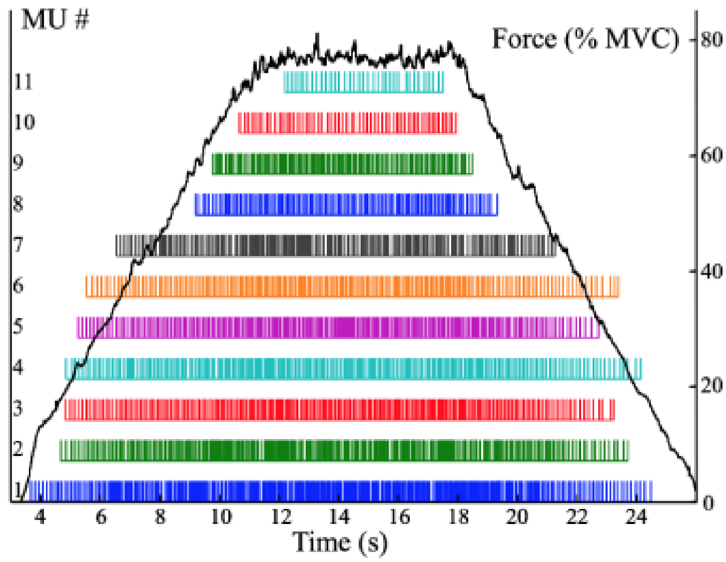


Figure 7 : Firing times bar plot acquired by the decomposition method in [10]. MU stands for motor unit; MVC stands for maximum voluntary contraction. (From Nawab [37])

The important excitation of muscle information underlying limb movement can reveal by sEMG signal. The outcome of which is a typical direction of research to identify intervals of muscle activation in the sEMG signal.

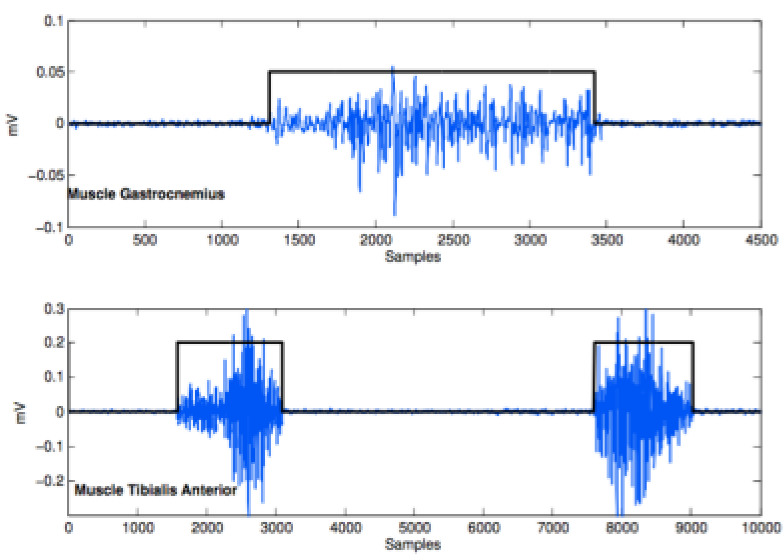


Figure 8 : The activity of muscle onset detection for clinical EMG signals [30]).

The onset detection of activity of muscle by an energy detector is shown as an example in figure 8 [30]. There are many different factors on which the shape of MUAPs depends as mentioned already above. It includes physical characteristics of electrodes, their position comparative to the muscle fibers that are active and electrodes arrangement. Also, temporal overlapping of different MUAPs makes an EMG signal because of which the actual EMG signal shape is hard to predict. In EMG processing, the major challenge is this property. But, the good thing is that the effective bandwidth of the EMG signal not rely on the shapes variability and can be supposed as past information of the EMG physiology, as illustrated in Figure 9. To develop the detection method of EMG signal, this prior knowledge will be used.

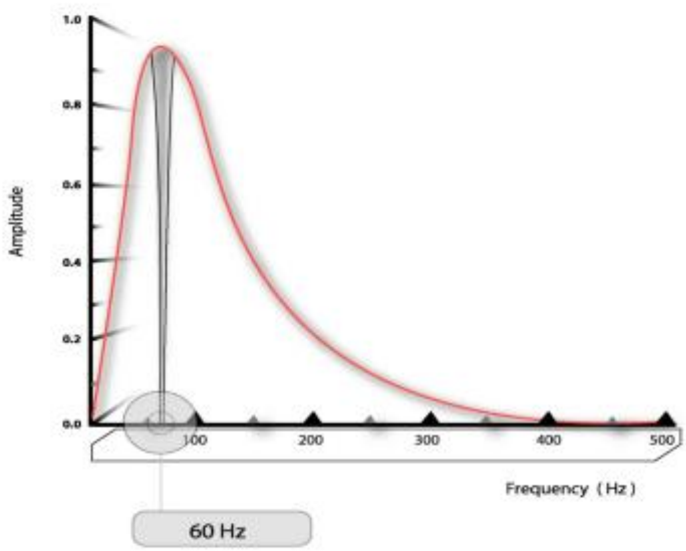


Figure 9 : sEMG power spectrum schematic representation [38]).

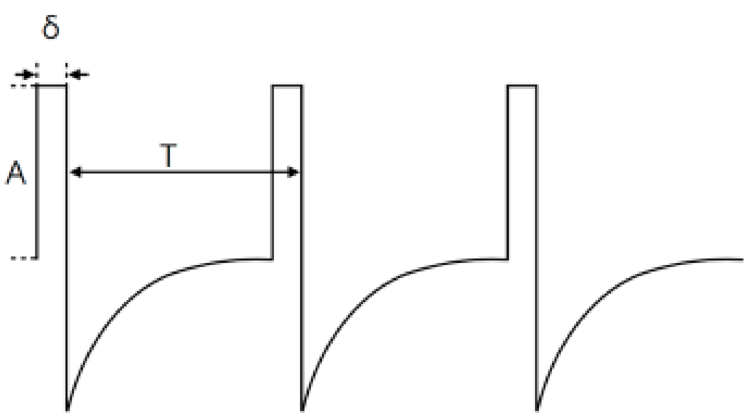


Figure 10 : Electric stimuli schematic

2.2 Characteristics of sEMG

The activity from multiple motor units, motion artifact, power line interference, skin electrode interference, and electronics circuit noise present in analogue front end and data converter are contained in the measured EMG signal on the skin surface. The main sEMG signals characteristics are as follow:

- The amplitude of the measured sEMG signal is in the range of μV to mV, mainly from 0 $mV_{pk\text{-}pk}$ to 10 $mV_{pk\text{-}pk}$ depending on the condition and muscle type [39, 40].

- The resting potential of sEMG signal is usually ~ -80/-90 mV [28, 29].

- There are two distinctive phases;

    - Transient phase monitored by a phase of steady state [41].
    - Voltages may be either negative or positive during contraction. [42].

- The frequency bandwidth of a measured sEMG signal ranging from 0 Hz to 2000 Hz, with mostly power of the signal falling below 600 Hz (De Luca). The utmost important activity bandwidth is in the range of 5 – 500 Hz while further bandwidths like 250 – 450 Hz are used subject to application and interest area [29, 43 – 45].

    - The complete usable range is 0 – 500 Hz [46, 47].
    - The most important spectrum is 50 – 100 Hz [46].
    - In a frequency range that is between 600 Hz to 2000 Hz, there is mostly noise present in this signal and it is very challenging to discriminate signal noise.

- The sEMG signal might be modeled as a non-stationary random process [42, 46].

- The sEMG signal is a combination signal of each and every potential of a muscle fiber near or beneath the every electrode [46].

- The measured sEMG signal required further signal processing to convert the signal into a signal which can be used in an EMG processor.

2.3 Issues of Signal Processing

The key issues that must be measured from signal processing standpoint are as follow:

- The electrode movement in relation to the skin causes motion artifacts. It is typically 0 – 20 Hz [42, 46].
- Quasi-randomness of firing of motor unit [42, 46].
- Design of an electrode (mainly circuitry design self-interference) [42, 46, 48].
- The muscle fibers that will be targeted is determined by the placement of an electrode and precise anatomy differs between individuals significantly [49].
- Nearby muscles cross-talk [31].
- Action potentials of muscles are altered by the muscle fatigue [49, 51].
- Electrocardiography (ECG) signals interference when electrode is placed near the heart [29].
- The noise or interference of power supplies or nearby equipment. It is normally 50 Hz – 60 Hz.

2.4 Applications of sEMG

The main applications of sEMG are as follow:

- Human – Computer Interaction is one of the main applications of sEMG that has the possiblity to offer a more ordinary interface for supervising different devices and computers. Also, it can develop the considerable interaction experience for physical disabled users.

- Rehabilitation and physiotherapy are also an example of sEMG application as the skeletal muscles activity may help a doctor in analyzing or determining that whether muscles of a patient is working correctly or not which can be decided by a recorded electromyogram. Study is being done to automate the recognition of a recorded electromyogram beyond simple use of human-in the-loop [51] which makes an assessment and gives feedback to a doctor and also a part of neuro-rehabilitation where a malfunctioning muscle tissue can be targeted by a stimulation [52, 53].

- Prosthetic Control is also an application of surface EMG, and it is also a growing area in this field [54]. As it does not cause neural scarring, it has the benefit over neural interfaces. Also, specifically for the prosthetic control, it is promising for muscles and new clusters of nerve to be mature through techniques like muscle re-innervation by targeting [55].

- Robotic Control: To control humanoid robots, e.g., arms of robots in a natural way, it is likely to record EMG signals. It is important to consider the interaction in this more natural way with robots as it decreases the time of training for operators. To improve the user comfort and the system utility, an interface has been shown in robotics of exoskeleton which is being capable to control an instrument without any necessity for a traditional link [56].

- Facial expressions recognition and without audio speech credit for use in study of psychology [57, 58], real-time translation of sign language [59], new diagnostic tests for diseases [60], and design for lower-limb amputees for fall prevention mechanisms [61] are other uses of EMG being explored.

2.5 Overview of Machine Learning

Let consider the "Machine Learning" definition to be the branch of study which gives ability to machines to acquire without being obviously programmed in the context of this thesis. This definition of machine learning is credited to Arthur Samuel (1959); machine learning plays the role of explicit encrypting by allowing it, which is to assist as the prediction technique. Other fields allied to it contain data mining and statistics. This work informs choices in how to design learners and choose them to make predictions by using analytical and statistical techniques and repeatedly draws attention on the literature of machine learning. The focus of this study is on the technique of feature reduction by taking in the classified sEMG data and planning a process that works almost same but with reduced features of sEMG for optimal accuracies.

2.5.1 Feature Engineering

The design and extraction of valuable features is typically the main phase in the "End-to-End" channel. The most useful way possible is to characterize the primary data which is the main idea of study. This can reduce the load of complexity, computational, and informational on any predictive algorithm used as well as aid the data interpretation, which also improves the performance of algorithms typically.

As high-performance features frequently eliminate collinear and redundant statistics in the data, extraction of feature is too nearly linked to reduction of dimension. Similarly, an aspect of dimensionality reduction often incorporate by useful features as this is an actual method of supporting algorithm in great performance learning estimate. The possibly composite bargains and relations with algorithms estimate involved in the assortment of all single features or combinations thereof, the extra load acquired by extraction and the necessity for handcrafting of the depiction (usually demanding knowledge of domain-specific) are the main feature design downsides. The features issue is well emphasized in classification of sEMG by the exertion in efforts to relate them in the literature and great number of features proposed. The diversity in capture devices and experimental procedures used is the reason that it is difficult which decreases the ability of a researcher to create computable evaluations [43, 56 – 57]. This is additional to the normal issues of loss of information from dimensionality reduction and interaction of feature classifier. These issues further worsen by the lack of availability of data from many potential studies. While for the algorithms benchmarking and competitions such as Imagenet, fast progress has made on the shared data sets basis by the community of computer vision [58].

2.6 Extraction of Surface EMG and Its Classification

Surface EMG classification and extraction of features was first studied in the 1970s. These are the major standards in control and design of prosthetic devices. The research in this field has been expanding very rapidly. This has involved protocol of signal acquisition (selection of muscle, placement of electrodes, and techniques of data acquisition), extraction of features (reduction or segmentation) for classification purposes mainly.

2.6.1 Feature Extraction

The essential part for classification is strategy and selection of feature extraction, particularly in study of neuromuscular EMG study and fatigue. The key aim is to enhance precision and robustness of classification. The features that contained information can be characterized as specifically individual, derivation or group as multi-features from both classes. It has to be extremely responsive and selective to the phenomena of study. It can minimize the problems of computational load's and will help in the real-time as well as offline applications.

It is normally agreed that that single feature provide less comprehensive information as compared to any multi features [59]. Therefore, after the identification of features, there is necessity for the process of feature reduction. As another factor, this is believed that the performance of classification will be affected by it [60], and the key to improve performance of classification is the choosing stage of robust features, but not the classifier.

The weak signals of EMG are recognized as a variable of non-physical, where the MF assessment wishes to be discovered from the measurable signals of EMG physical variables as other definable pointers. The Amplitude of EMG signal observed MF only if there is decline in both features of FD and a rise in the TD features [61].

2.6.1.1 Analysis Domains

There are various fields in the sEMG analysis that might be utilized in combination or individually. The identification of features and domain investigation were considered as the major standards in the study of surface EMG [62]. The most conventionally used descriptive time domain (TD) statistic features are slope sign change (SSC), root mean square (RMS), zero crossings (ZC), waveform length (WL), feature related to TD autoregression (AR), and maximum amplitude value (MAV). The frequency domain (FD) features that are considered are mean frequency (MNF), median frequency (MDF), and peak frequency (PF). The several features of time frequency domain (TFD) are stated to stun the characteristics of time-varying of the signals of EMG and applied in numerous studies such as continuous wavelet transforms

(CWT), Wigner-Ville distribution (WVD), and short time Fourier transform (STFT). Table 1 highlighted the strength and weaknesses for analysis of each domain.

The features that are most useful in the TD have been proposed by Hudgins et al. (1993) [63]. But those features do not suit with time varying performance of the EMG signal. Numeral studies have successively been described using TD, FD along with TFD techniques. The assessment and comparison of the fulfillments of these methods with extracted features were already carried out. But the study for determining the best features was not performed.

Domain	Advantage	Drawback	Notes
Time	Easy implementation, simple, and low computational cost	The non-stationarity (time-varying) property of EMG signal cannot be handled.	Because of low complexity, most cases preferred TD features which is desirable for implementation in real time.
Frequency	Suitable for EMG signals and good frequency localization	Some features of FD have the same discrimination in TD.	"FD based EMG features are not good in classification of EMG." [64]
Time-Frequency	Good frequency and time resolution.	Expensive, complex, and require more processing time.	"The TFD and TD features performance is similar." [65]

Table 1: The EMG signals domain analysis

It is suggested in the study that FD based EMG features were not decent enough in classification of signal of EMG [64]. In this study, a detailed theoretical background and review of 37 features were given and to avoid redundancies in the EMG features, the study pointed out the suitable features in the EMG study to be used. Though the MF wasn't into the consideration in the study because of different approach that may suggest a new understanding in the study.

2.6.2 Feature Classification

For control purposes, surface EMG classification offers more perspective and trustworthy information. It is agreed in general that several algorithms of classification like linear discriminant analysis (LDA), support vector machine (SVM), artificial neural network (ANN), extreme learning machine (ELM), k nearest neighbor (k-NN), multi-layer perceptron (MLP), and others give a same act in terms of precision. There remain other ideal features and sets for suboptimal feature that are yet to explore for classification.

Ten isometric contraction classes were classified by Hargrove et al. in 2007 from iEMG and sEMG simultaneously collected [65]. The conclusion was that there is no distinction in precision of classification from both EMG muscles types. The quantity of channels should be in between three channels were suggested by them to achieve optimal accuracy of classification. A unique system of classification for the purposes of rehabilitation using two classifiers combination that are Fuzzy Inference System (FIS) and Artificial Neuro Network (ANN) is designed by Khezri and Jahed in 2009 which yielded a new Adaptive Neuro-Fuzzy Inference System (ANFIS) [66]. The algorithm of classification that was proposed generated valuable identification successfully for six hand movements' types.

The classification performance of multi features built on the algorithm of feature reduction Mutual Component Analysis (MCA) has been investigated by Khushaba and Kodagoda in 2012 [67]. A satisfactory result yielded by the developed feature reduction. Like this work, several other studies have been done with different technique of feature reduction [68 - 70]. There is a big interval institute in the methodology of the study with proposed features in these researches despite modern development and research case studies discussed in Bai et al. in 2019 [71, 72].

To achieve better performance of classification by an instinctive approach is thus needed. Based on several aspects of the classification and features extraction protocol for signal acquisition, a new policy adopted by this study. In the preliminary study, approaches that employed were frequency and time domain (FD and TD). The study also looked into time-frequency domain details using wavelet transform. For signals like EMG, the most useful technique for analysis is wavelets. A time-varying signal component of frequency and time require wavelets. A well time and resolution frequency is presented for the classification system. The gap between different studies was improved by these approaches.

2.7 Feature Reduction

To ease the classifier of too much computational load and for better results of classification, a method of feature reduction can be used especially when the feature space is huge as wavelet-based features case [48]. The method of reduction of feature can be categorized in two: feature selection methods and projection of features. The difference between the two is that in feature selection, most suitable features from the set of unique feature set is chosen by an algorithm whereas in projection of features, there is a transformation from a large dimension feature set into a smaller dimension [73]. The pattern of EMG recognition with wavelets for research has been done much by feature projection [74 – 78].

2.7.1 Feature Selection

Though PCA was used to outperformed feature selection [79, 80] it has been rarely used in publications. To minimize the space of feature after a so called harmonic wavelet packet transforms (WPT), a Genetic Algorithm (GA) was applied by Wang et al. [81]. The coefficient of energy and ANN classifier were used by them. They trained the GA from the classifier feedback. The GA found optimal features and after that again the ANN classifier was trained with these features.

In combination with projection of features, a feature selection is used in the work of Xing et al. [82]. The packets energy from WPT were utilized as features and then based on a function of discriminative criterion, the feature selection was made. Kuo and Langrebe introduced Non-parametric Weighted Feature Extraction (NWFE) to reduce the space of feature for further dimensionality reduction [86]. An improvement to projection of feature with LDA was introduced by NWFE method. However singular matrix inverse calculation occurs when applied to WPT energy features. To avoid this matrix from becoming inverse of a singular, a recursive feature selection algorithm was implemented by them. This method was deployed for virtual hand controlling and showed promising real-time results.

2.7.2 Feature Projection

The features can be arranged for example by their ability of discriminative or variance while transforming the feature space by a method known as feature projection. The methods of feature projection are categorized into supervised and unsupervised. Mainly, supervised with

LDA and unsupervised with PCA. The features are sorted by discriminative ability with LDA while they are sorted according to the transformed features variance in PCA and then for instance 90% features can be selected to hold based on the total variance and others can be discarded [75]. Englehart et al. showed in their work that the better classification of feature projection is given by PCA than feature selection with class separability Euclidean distance criterion [82, 83].

An improved PCA functionality by Chu et al. is given by linear transformation with Self-Organizing Feature Map (SOFM) of nonlinear [77]. They take advantage of coefficients of WPT and MAV as features. The accuracy of classification delivered by combination method of PCA and SOFM was higher than with only PCA without significantly increase in time of processing. The accuracy of highest classification yielded by SOFM alone but it increased processing time greatly. This was the reason that firstly feature set reduced by PCA and then SOFM. There was also an argument by Khushaba et al. that if non-linear part comes before occurring of PCA then it could be further improved [78]. Because of this, they applied Fuzzy C-Means (FCM) algorithm and not used SOFM for features clustering based on their separability of classes. Only those features were selected from the clusters that backed to the classification and further compact by PCA. They used MLP classifier and WPT with packets of energy as features.

Another method evaluated by Chu et al. in another research which was a supervised feature of projection [84]. The feature projection based on LDA method was implemented which outclassed both the SOFM and PCA in terms of classification precision and processing time.

Both PCA and LDA feature extraction performances were also compared by Zhang et al. and they concluded the same that PCA was outperformed by LDA [79]. Another approach was implemented by them in which they combined two methods, but they did not get the improved results as much as related to only using LDA. They executed this in real time with MLP classifier on a prosthetic hand prototype. The real-time recognition of hand gesture showed promising results with it.

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CHAPTER 3: METHODS

This chapter includes methods based on pre-processing, feature and classification to keep up the work in this study that were not considered in the earlier chapter.

3.1 EMG Pre-Processing

In previous chapter, the model representation and the unique basis of EMG signal, the MUAPs initiation for EMG signal, obvious the activation of neuromuscular by contraction of particular muscle and permissible EMG model realization were discussed. To interpret the information enclosed within the EMG signal based approach is the main issue in examining the EMG.

The study aim based on pattern classification of EMG is presented in this chapter. This forms the base of the effort in this theory. In Chapter 1, the block diagram of an overall study was presented. First stage is initialization of the classification of pattern for the research starts by conditioning the signal with appropriate techniques of preprocessing such as segmentation of signal and filtering. Extraction of features will take place in second stage as best representation of the content of EMG information is by features. This will contain the standardization and reduction of feature. As a way to form the result, classification of pattern is implemented in next stage. At the end, method efficiency for pattern classification estimation is assessed through classification analysis.

3.1.1 Signal Conditioning of EMG

Different systematic methods for the signal or data are implemented in this thesis work. This includes the segmentation and process of filtering like removal of noise of direct current from the signal. As the primary significant features are the segments lengths that require to be concluded, segmentation will be performed [90].

There are two kinds of segmentation scheme generally for EMG investigations. One is the disjointed scheme and the other is an overlapped scheme. Neighboring or adjacent sections for the extraction of feature of a selected range will be used in first scheme that is disjointed scheme. Whereas in the second scheme that is overlapped scheme, an overlapped section of the existing with addition of time need to be lesser than the range of selection.

The illustration of the two segmentation techniques that can be used in EMG signal handling is shown in figure 11.

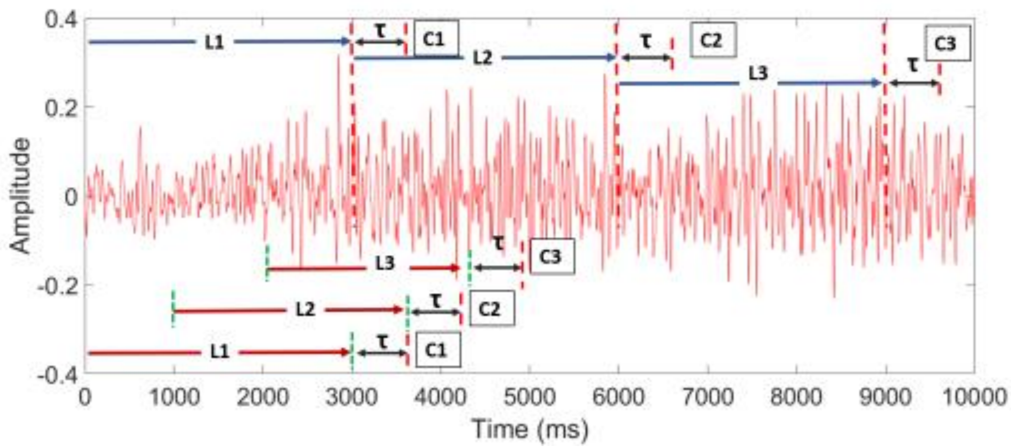

Figure 11 : The example of strategy of segmentation

The blue arrows are used to label adjacent and disjointed segments with the marker L that represents EMG signal segment length for extraction of features. The time required for feature extraction and classification method is represented by τ. Seconds later, classification decision C is decided. Moreover, red arrow represents scheme of overlapped segmentation.

The segment that is overlapped was used for the segmentation of EMG signal in this study. The chosen segment length is related to the minimization of computational problems and the characterization establishment of multi-region. Studies have showed the trade-off between segment range used and classification time for processing [91 – 92]. They have established the statement that classification performance will be affected by configurable parameters which are time delay and length of a window. The EMG signal preprocessing sacrifices time response but improve the accuracy.

Before the procedure of feature extraction, EMG signal were digitally preprocessed. An epoch window of 5s for every movement was used to minimize the processing complexity by employing a technique. The signal selected for each movement of an arm is of 5s and combination of all movements was in particular order so that they were correctly labeled. An illustration of it is shown in figure 11. As the requirement of continuous control of prosthesis is extraction of feature in a sliding window manner so this type of preprocessing system is employed. The hand and arm movement task performed by a subject is 5s time frame is the requirement of acquisition protocol used. The reason to use epoch of 5s fragmented window is to certify that no information was ignored. In the process of feature extraction, increment of overlapped window of 100ms was used for the entire signal.

3.2 Feature Extraction

The most significant portion considered for the signal analysis is extraction of feature as it provides the most compact and useful indicators set when dealing with compressed signals such as EMG especially. A set of data containing most information in reduced size will be produced by the process of feature extraction which is required in many signal analysis for the basic raw signal representation. Every segment details the data of EMG and are represented by the EMG signal features which allow the reliability of system. Also, robustness of it will not be discussed. The process of extraction of feature yield complete feature sets by combining every time window at particular channels of EMG in global vector to represent pattern of an EMG for certain task or movement. It is stated by the Hargrove et al. (2007) that a stage of extraction of feature is critical as it is the method of mining the exceptional and valuable data that relies on the signal of an EMG [93]. As a result, it will give better class separability. It is believed by several researchers that the flawless selection of EMG features is far superior to a worthy classifier. Many utilized numerous techniques of extraction of feature.

3.2.1 Features of Time Domain

The most generally and advantageous features used in many studies of classification are time domain (TD) features. The minimum level of complexity associated with procedure of extraction and outstanding in performance compared to other processes like FD and TFD are the primary benefit. The importance and usefulness of TD have proved by many studies, specifically on their speedy and cool implementations, and also without any need of alteration [90, 94 – 96]. There are also drawbacks of TD and one of major among them is the generation of features from the signal stationary properties. Mostly EMG captured in dynamic movements and there may be very high variations as it is dealing with non-stationary signal.

TD features are very vulnerable to noise acquired during collection of data as it is calculated solely based on the amplitudes of EMG. The extremely important is spectral and temporal information for class movement's differentiation. Also, distinguishing of performance of both TD and FD in classification is the main criteria of it. Most of these features have been utilized by many researchers and it is to mention that these all features are not implemented together. For the study of classification, features are selected. The features of TD suggested to be used in this thesis are six and are briefly defined in following subsections.

3.2.1.1 Root Mean Square

Root mean square (RMS) is modeled like method of Gaussian which is similar to the contraction process of usual muscle [97]. The standard deviation (SD) procedure also resembles with it [98]. The model of RMS in mathematical form is defined as follow:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2} \qquad (3.2.1.1)$$

Where,

x_i = EMG signal.

N = Signal sample number.

Among the highly recommended features used with analysis of EMG is RMS.

3.2.1.2 Integrated Absolute Value

One of the most generally used in the study of EMG signal and well known by researchers is Integrated Absolute Value (IAV) feature. It is computed using the EMG rectified by the moving average and is also to be called as Integrated EMG (IEMG). Other names of this feature are Mean Absolute Value (MAV), Average Rectified Value (AVR), Average Absolute Value (AAV), and the v – order of first order ($V1$) [96, 98]. The model of IAV in mathematical form is given as follow:

$$IAV = \frac{1}{N}\sum_{i=1}^{N}|x_i| \qquad (3.2.1.2)$$

Where,

x_i = EMG signal.

N = Sample number of the signal.

3.2.1.3 Zero Crossing

The frequency related to analysis of time domain is known as zero crossing (ZC). It is a component of spectral measurement where the magnitude of EMG in number permits the level of amplitude of zero [94, 98]. The condition of threshold is applied to overcome background noise or low-voltage fluctuations. The model of ZC in mathematical form is defined as follow:

$$ZC = \sum_{i=1}^{N-1} [sgn\,(x_i \text{ X } x_{i+1}) \cap \; |x_i - x_{i+1}| \geq threshold] \tag{3.2.1.3}$$

$$sgn\,(x) = \begin{Bmatrix} 1 \\ 0 \end{Bmatrix} \left| \begin{matrix} if\ x \geq threshold \\ otherwise \end{matrix} \right\}$$

Meanwhile, individual feature processes the relation of ZC uphill divided by peaks number (NP) [100] which can be measured only by their Spectral Moments (SM) that is discussed in 3.3.2. The representation of corresponding feature can be as:

$$IF = \frac{ZC}{NP} = \frac{SM_2}{\sqrt{SM_0 \text{ } X \text{ } SM_4}} \tag{3.2.1.4}$$

3.2.1.4 Waveform Length

The complexity of EMG measure is waveform length (WL). It is well-defined as the accumulative sum of overall differences above segment of every time of a signal. This feature is defined as wavelength (WAVE) by some researcher. It is also known as signals absolute derivative total value. The WL formula is as follow:

$$WL = \sum_{i\,=\,1}^{N-1} |x_{i+1} - x_i| \tag{3.2.1.5}$$

Where,

x_i = EMG signal.

N = Sample number of the signal.

The waveform length ratio (WLR) may be another feature that is quite close to WL and useful in this thesis. The ratio of the first derivative of WL feature to the second derivative of waveform length is known as WLR. It is defined mathematically as follow:

$$WLR = \log\left(\frac{\sum_{i=0}^{N-1}|\Delta x|}{\sum_{i=0}^{N-1}|\Delta^2 x|}\right) \tag{3.2.1.6}$$

3.2.1.5 Slope Sign Change

It has mutual eccentric as ZC feature. Slope Sign Change (SSC) is the representation of information of frequency signal by calculating its changes [94]. The slopes of changes in positive and negative are calculated inside their purpose of threshold within three sequential. This will remove EMG background noises. It is defined mathematically as below:

$$SSC = \sum_{i=2}^{N-1} \left[f\ [(x_i - x_{i-1})\ X\ (x_i - x_{i+1})]\right] \tag{3.2.1.7}$$

$$f\ (x) = \left\{\begin{matrix} 1 \\ 0 \end{matrix} \middle| \begin{matrix} if\ x\ \geq threshold \\ otherwise \end{matrix}\right\}$$

The parameter threshold value of that feature suggested to be selected is inside range of 50 µV to 100 mV [97, 99]. However, it may vary if background noise and instrument setting for the gain value are not level.

3.2.1.6 Auto-Regressive Component

The approach of statistical based on the EMG signal spectral information knowing the location of peak is auto-regressive feature. It is basically an estimate model which defines EMG signal as a previous samples linear combination x_{i-p} and a white noise w_i [97, 99]. The coefficient of AR is employed in many classification models as feature vector. Mathematically, it is defined as follow:

$$x_i = \sum_{p=1}^{P} a_p x_{i-p} + w_i \tag{3.2.1.8}$$

Where,

$P =$ AR order at specific coefficient of autoregressive.

$a_p =$ Coefficient of autoregressive.

It has been suggested in research studies that for EMG analysis, the best order of AR to be used is between fourth order (AR4) [97, 99] to sixth order (AR6) [90, 93]. The writer chooses AR6 to be used in this study as one of the features of TD. The analysis of movement of hand and finger flexion was best tested with AR6.

In this study, all the six TD features have been used extensively by scholars as already above cited. The AR with mixture of features of TD has been suggested and used in earlier study [102]. The better works have shown by them in achieving the feature and EMG signal classification.

The very high classification accuracy proved by these features in comparison to any FD and TFD in detection algorithm of movement of hand [93]. This has been the motivation as already described earlier to select TD features for this study and for request into the signal of EMG composed within this research framework.

3.2.2 Features of Frequency Domain

The other way that may be used for EMG signal analysis is frequency domain (FD). The representation of a function of time transformation to the sine waves function of integral or sum with different bands of frequencies is spectral components of a signal or frequency. The familiarity of this exploration is well identified in different studies mainly with respects to the EMG signal. It is unlike to TD as it shows range or frequency band in which signal lies while change of signal over time is shown by TD.

The FD transformation is resulted by the Power Spectral Density (PSD) or the spectrum. It is used to study recruitment of MUAPs mostly [103 – 105] or fatigue analysis [106 – 107] for EMG signal. The tool that is most useful for signal frequency component studies is PSD. The statistical properties have been functional using different approaches to the PSD and are well defined as Fourier Transform. The periodogram or other parametric methods can be used for estimation of it.

The two features of FD or PSD variables which include Mean Frequency (MNF), and Median Frequency (MDF) have been extensively used in numerous research studies. The other variables of FD that are suitable and may be used are Mean Power Frequency (MPF), Peak Frequency (PF), central frequency, frequency ratio, Total Power (TP) and spectral moments.

In this study, therefore, six features of FD are selected for analysis. The description of these FD features is below:

3.2.2.1 Peak Frequency

The frequency that maintains the full power spectrum is known as peak frequency (PF). It is given as below:

$$PF = max\left(P_j\right), j = 1, \ldots, M \qquad (3.2.2.1)$$

Where,

P_j = Power spectrum.

j = Frequency bin.

3.2.2.2 Mean Frequency

The summation of power spectrum from the frequency and EMG signal divided by the intensity of total spectrum is known as the normal value of frequency which is actually a mean frequency (MNF) [90, 98, and 108]. It is also recognized as spectral center of gravity and central frequency. Mathematically, it is expressed as follow:

$$MNF = \frac{\sum_{j=1}^{M} f_j P_j}{\sum_{j=1}^{M} P_j} \qquad (3.2.2.2)$$

Where,

f_i = Spectrum frequency.

P_j = Power spectrum.

j = Frequency bin.

M = Frequency bin length.

3.2.2.3 Median Frequency

Median frequency (MDF) is defined as the frequency spectra division of two equal amplitudes. This frequency type can also called as half of total power.

$$\sum_{j=1}^{MDF} P_j = \sum_{j=MDF}^{M} P_j = \frac{1}{2}\sum_{j=1}^{M} P_j \tag{3.2.2.3}$$

3.2.2.4 Mean Power Frequency

The EMG spectrum average power is a mean power frequency (MPF). The MPF model in mathematically representation is as follow:

$$MNP = \frac{\sum_{j=1}^{M} P_j}{M} \tag{3.2.2.4}$$

3.2.2.5 Total Power Frequency

A power spectrum aggregate of the EMG is known as total power frequency (TPF). Mathematically, it is written as follow:

$$TPF = \sum_{j=1}^{M} P_j = SM_0 \tag{3.2.2.5}$$

The other name of TPF is spectral moment of zero order (SM_0) and can be represented as the energy [108]. If we put *n* equals to zero in the above equation then it will be known as Parseval's theorem. That is why; the symbol in the spectrum of frequency for total power is SM_0 [109].

3.2.2.6 Spectral Moment

The power spectrum extraction from the EMG signal can be done by another way known as spectral moment (SM). It is a type of approach built on statistical analysis that will yield a power spectrum based new feature. The general order of SM_n definition is given below:

$$SM_n = \sum_{j=1}^{M} P_j f_j^n, n = 1, \ldots, n \quad (3.2.2.6)$$

Where,

$n =$ SM order number.

In this study those features are selected for use that enable control based on EMG, show speediness in a noisy environment, manage maximum separability of class, and are linked with low complexity computation. This is much needed to make better classification of pattern performance in EMG.

To use TD or FD individually is not sufficient for extraction of features as EMG signal include non-stationary or transitory characteristics. The whole analysis of time series in one off is given by Fourier series.

3.3 Statistical Analysis

The value of purpose clarification of endpoint objective must be goal of scientific study in many thesis studies. The values study level will be determined by this endpoint that may have the indication of their works. The method that is one of the best is descriptive statistics to achieve main goal. In order to adopt a model, researchers may become habitual by using statistical purposes as a model. To present data by organizing and compiling in a clarifying way is done by descriptive statistics in some way. The impact of it will end in abnormalities in the study results, if this is not taken into consideration in the course of study concerning data of extensive scale.

3.3.1 Descriptive Statistics

It is to be called as a prior condition in evaluations of hypothetical or in inferences making and necessary for various studies involving analysis of biometric [110]. The well-presented data to get more understanding of study for the researcher's subject is produced by a process known as descriptive statistics.

3.3.2 Correlation Coefficients

The specific monotonic relationship case is a linear connection between two variables. The "correlation" term between two continuous variables is used such a linear relationship context mostly.

The coefficients of correlation can be found out by using most commonly two types in the biometric analysis. These are known as coefficient of correlation of spearman's rank and coefficient of Pearson's product moment correlation. The variables type determines the correct type of correlation coefficient being studied [111].

The identifying approach of the tradeoff, association, or relationship among two or more variables is defined as correlation. The irrespective of linear or nonlinear statistical method to measure any possible association of two variables is a mathematical definition of correlation [112]. The linear strength of computation and relationship amongst variables studied pointed out by correlation coefficient. The two variables closeness that are co-vary is statistically calculated by it. It just represents as +1 for the excellent positive correlation and -1 as perfect negative bond. While over 0, it means there is completely no correlation.

3.4 Time Frequency Domain

3.4.1 Fourier Transform

Joseph Fourier in his study of spectral introduction found wavelets. The Fourier synthesis had been elaborated by him which is switching method of TD, as denoted in TD (*x(t)*) to FD (*X(f)*) as shown in below figure 12.

Figure 12 : The general practice in time series signal measurement is known as Fourier transforms (FT).

The Fourier series for whichever periodic waveform (2π) can be commonly denoted as:

$$x(t) = a_o + \sum_{k=1}^{\infty}(a_k coskt + b_k sinkt) \tag{3.4.1}$$

While the indications for a_0, a_k, and b_k Fourier coefficient are as follows:

$$a_o = \frac{1}{2\pi}\int_0^{2\pi} x(t)dt \tag{3.4.2}$$

$$a_k = \frac{1}{\pi}\int_0^{2\pi} x(t)coskt\, dt \tag{3.4.3}$$

And,

$$b_k = \frac{1}{\pi}\int_0^{2\pi} x(t)sinkt\, dt \tag{3.4.4}$$

$$X(f) = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}\, dt\, ; j = \sqrt{-1} \tag{3.4.5}$$

The main result of Fourier discovers the invisible signal spectral components which makes it valuable and excellent in general analysis of a signal. The significant drawback known is that it explored the complete signal at once because of FT nature. The exhibited frequencies are not localized in time and are inadequate is the concern of this drawback. It can be seen in below figure 13.

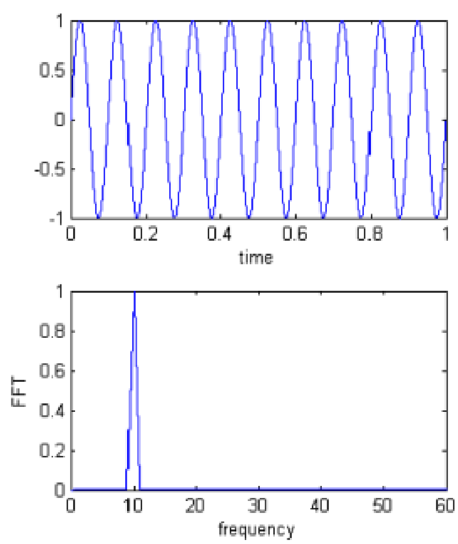

Figure 13 : Fourier series of a signal in TD is shown in top figure while bottom figure show signal in FD.

The application of system based on real-time is not realized easily and it is difficult to know that when and where a specific situation develops.

The TD localization details get compromised while the window is wider and the details of localization in FD get compromised while the window is narrower. This is known as uncertainty principle effect. The STFT equation can be stated as follow:

$$X_{ST\,FT}(\omega,\beta) = \int_{-\infty}^{\infty} x(t)h(t-\beta)e^{-j\omega t}\,dt \tag{3.4.6}$$

Where,

$\beta =$ The central point of time window.

The dependency of the resolution of frequency and time is on the size of the window and the content of regional frequency is provided by STFT. The shorter time window up to a restricted amount like as quasi-stationary for a particular time. By mean of this that window size is necessary for precision measurement which is the disadvantage of this method. The unproductive way of localization time-frequency is revealed by STFT due to its operation "response interval" or scale.

3.4.2 Wavelet Transform

Another improved version of FT is described as wavelet transform (WT). In this section, other aspects and links between WT, STFT, and FT with regards to properties are explained. In order to gain precise look on characteristics of wavelets, algorithm observations are defined.

The first strategy is determined by the scale in wavelets investigation, one kind of TFD analysis. Besides, many practices in signal interpretation and numerical designations performed by methods are recognized as wavelets. The signal dataset is run at numerous instances of dilation and translation by algorithms of WT. A large window can be used for viewing the vast information in detail. Similarly, small window can be used to view the small information detail. The result analysis estimation in the structure of both the trees and the forest is showed by WT.

The WT investigation method, several debate and opinions of WT approaches are covered and unveiled in current section with analysis decoration of WT in previous described reports Bruce et al. (1996) and Englehart et al. (2001) [113 – 114]. The new passion among scholars in data processing and analysis of signal has been caught by WT.

WT are the best for processing of signal for multiple applications. It is also pre-eminent when applied in different directions like communication, transient study, and signal. The satisfied outcome is given by WT to the FT and STFT dilemmas. It is referred to below figure 14.

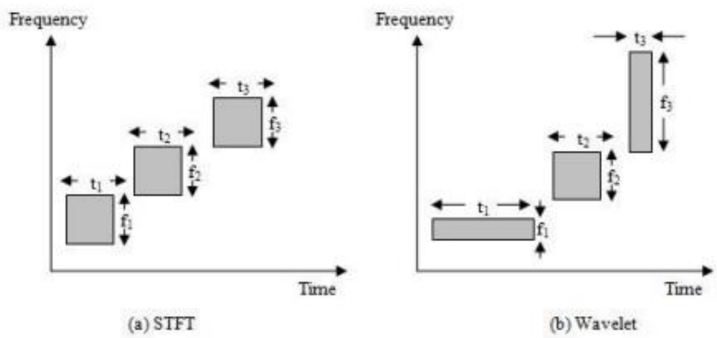

Figure 14 : The approaches of WT are different to the STFT as it enforced a timely adaptable window [115]. The essential properties of localization of frequency in both TD and FD are produced by WT technique.

Because of the fixed size window, resolution of fixed frequency and time is produced by STFT for the entire signal. In contrast to it, WT produces window of different size given that various resolutions of frequency and time [115]. A "dissociations" process of a signal has exhibited by the ultimate method of WT property. A decomposition of power signal with specified coefficients detail is represented by it. Though, wavelet function width differs with every spectral component, it provides and computed coefficients details for every window made.

The regular series of FT is described as WT which is working one scale either frequency or time, it works for both time and frequency on the basis of multi-scale. The decomposition of raw signal into components of scaled and decoded known as coefficient is done mother wavelet. The STFT flaw which use window of fixed size overwrites by this process. The illustration of overall process of WT is shown below in figure 15.

Figure 15 : The process of WT in general approach

The function of zero mean is basically known as mother wavelet or wavelet function ψ (t) and satisfies the condition of admissibility:

$$C_\Psi = \int_{-\infty}^{\infty} \frac{|\Psi(\omega)|^2}{|\omega|} d\omega < \infty \tag{3.4.7}$$

Where,

C_Ψ = Admissibility constant.

$\Psi(\omega)$ = Fourier transform of the wavelet function.

The procedure to be "admissible" should be centered and zero averagely in both space of frequency and time which represent the mother wavelet application. The condition of admissibility will be satisfied by this in WT. One can define the WT window function as $\psi_{ab}(t)$:

$$\Psi_{a\tau}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-\tau}{a}\right) \tag{3.4.8}$$

Where,

a = Scaling factor.

τ = Translation parameter (time shift).

The scaling factor "a" must be positive while a, $\tau \in \mathsf{R}$ and $a \neq 0$. The mother wavelet represented as the position, $\tau = 0$ and scale $a = 1$. The other wavelets can be produced by utilizing these at several translation and scale.

3.5 Feature Reduction

It is crucial to implement feature extraction method to draw important embedded information and delete undesired interferences and component from the signal of EMG. The adoption of feature vector is important as successful classification greatly depends on it. However, several classification investigation of the EMG signal has utilized a set of features that has conceded some redundant features. Then, for analysis of EMG, the employment of feature reduction strategy is a basic need.

A great degree of harmony in their dimensionality or attributes could be shown by extracted features. It is therefore a need of reduction technique that may able to reduce the dimensionality feature. Different methods include Principle Component Analysis (PCA), Linear Discriminant Analysis (LDA), and independent component analysis [116]. One technique that is PCA have used in this thesis for the assessment of features performance.

The methods of feature reduction comprises of representation of low-dimensional feature with capability of improved discriminatory that are of main interest. There are various approaches that have been examined for extraction of feature and dimensionality reduction, such as PCA, LDA, and ICA. To resolve dilemmas of classification especially, LDA is designed. It aims to increase the determinant proportion of calculated units of between-class sets to the between-class sets determinant of the units of computation.

Reduction of feature has been recognized as “curse of the dimensionality”, and has been used to remove correlated problems among vast feature vector dimension [93]. This problem arises with high muscle channels implementation. One can decrease the feature dimensionality problems with the help of feature projection. Feature projection also helps in creating a set of features that improves the performance of classification as well as the price of computational reduces.

In this thesis, one type of feature reduction technique is explored which includes PCA [117]. This technique will serve to reduce the feature dimension, computational price minimization and to provide a set of feature that improves the result of classification. In the following subsections, these two procedures of feature projection are presented.

3.5.1 Principle Component Analysis (PCA)

A method of conversion applied because of its easiness in pre-processing and analysis of a signal [118], feature reduction [119] and for assistive devices controller design [120] and rehabilitation systems [121] is known as principle component analysis. PCA is commonly adopted and an established method in various works of research involving bio-signals [122], and is introduced as an approach of standard in classification studies. Recently, several modifications have been established to overcome the data dimensionality problems and for proper visualization of data in PCA.

The details of class label are not included in this procedure as it is depended on feature projection data. The matrix of data reconstructed statistically by PCA through process of diagonalizing by the matrix of covariance. The correlation between data variables is acquired by the method. The correlation within the variables manifested by the first few substances only if both variables evaluated and calculated are associated. The illustration of PCA computation steps are shown below in figure 16.

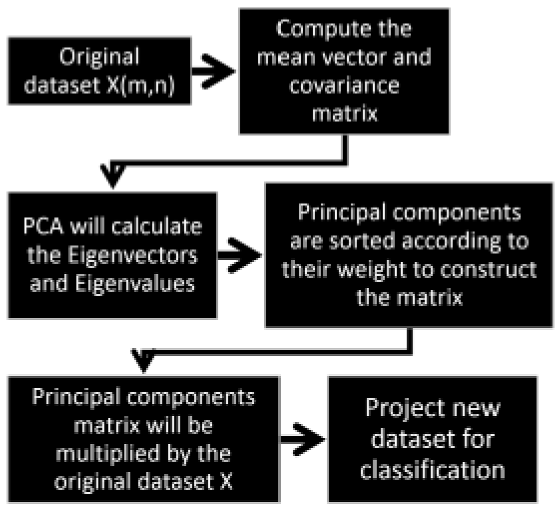

Figure 16 : The illustration of strategy for feature reduction problem using PCA.

Let consider a dataset X with number of samples n multiplied by m measurements.

$$X = n \times m \tag{3.5.1}$$

For the full dataset the mean vector of dimension (μ) and covariance matrix of X are computed by using subtraction. The covariance matrix eigen decomposition is calculated by PCA which will produce eigenvalues (λ) as the weights and principle components known as eigenvectors (W) sorted firstly with highest magnitude. The orthogonal components number is decided with the help of eigenvalues which makes them important for analysis in future, while the connection between original variables and new components will be established by eigenvectors. These are used in making the matrix of principle components and then multiplied by the set of data of original one. This will yield the new set of data for purpose of classification.

3.5.2 Uncorrelated Linear Discriminant Analysis (ULDA)

The technique recognized for problem of dimensional reduction and feature extraction is LDA. The utilization of it is in various studies such as analysis of sensors in recent years [124], text classification [126] and recognition of fingerprint [125]. A set of features having larger dimension varied into groups is accepted as an input by LDA by shaping the fine projection that highlight new features toward a space of dimension reduced in size while preserving the group composition. It maximizes gap between the classes and shrinks the gap between classes which as a result reach the highest separation.

A type of LDA which is acknowledged as Uncorrelated Linear Discriminant Analysis (ULDA) is another method of dimensional reduction engaged in this thesis. As discussed widely, LDA best isolate targets or classes by a linear variables combination [127, 128]. A classical LDA require matrices that are scatter to be nonsingular. Because of this reason, limitation problems and the lack of dataset de-correlation supervision, ULDA was suggested by Jin et al. in 2001 [129]. This will provide bad results while allocating with groups of great unnecessary info in sets of data.

The novel dimensional reduction tactic introduced by Jieping et al. in 2004 is named as ULDA which uses the technique of Generalized Singular Value Decomposition by generating uncorrelated features in the converted space to deal with data that is under sampled [132]. The provided details by them on ULDA have thus been useful in several exploration studies as a technique of projection of feature [130 – 131, 117]. The transformation steps are shown in below figure 17 for the ULDA technique of feature reduction.

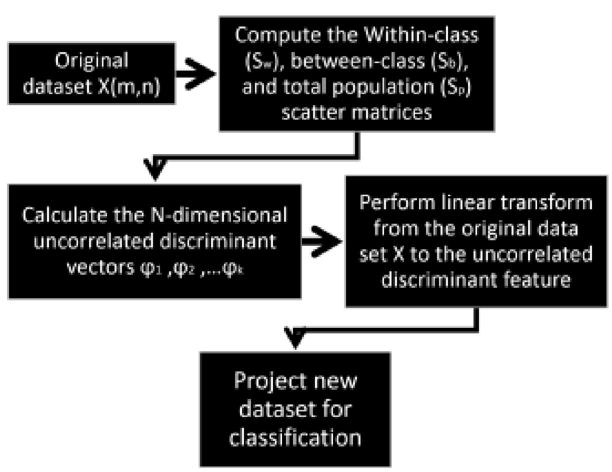

Figure 17 : The illustration of ULDA steps.

ULDA is a technique for extraction of feature that is supervised. It uses Fisher criterion based on analysis of discriminant. ULDA tries joined variables linearly described as vectors of uncorrelated discriminant while PCA discovers for objectives in the data that are of highest diversity. The separability between classes maximize by the vectors regarding the Fisher criterion. The constraint of so-called "S-orthogonality" must be satisfied by ULDA obtained vectors in matrix transformation is the key difference between LDA and ULDA [117].

3.6 Pattern Classification Strategy

The attention of corresponding level given to arm movements of less dexterous, such as grasping, elbow movement, and gross hand movements have not been gained by recognition of EMG pattern classification of hand movements. Also, the accuracy results of similar classification not give the same performance level. To analyze data input inside a representation of particular pre-defined sets for the movements of hand can be done by classification based EMG control. The several approaches involve by it for classification, feature extraction, and dimension reduction. The strategy of data collection applied also includes in the current study. The researcher utilized classifier types and feature sets to attain accuracy of high standard such as Artificial Neural Network (ANN) [109, 133 – 134], Linear Discriminant Analysis (LDA) [131, 135], and support vector machines (SVM) [136 – 137].

The structure of standardized classification has been employed in the last decades to analyze the EMG signals collected using sets of pre-stated movement [93]. Thus, various techniques of classification and feature type have been used in several examination studies showing the practicality of surface EMG mechanism [90]. The notion for strategy control continued by Tenore et al. in 2009 by using EMG based for flexion and extension of different fingers on movement of fingers using 32 channels EMG [139]. The excellent classification achievement is managed by them but cost them fortune in time processing because of the electrodes in large number. However, the compulsions for making state of the prostheses art would significantly reveal without discrediting the efficiency of classification by EMG channels modification.

The accuracy of classification analyzed by Hargrove et al. in 2007 [71] used methods of five classification pattern (multilayer perceptron, LDA, linear perceptron, hidden Markov model, Gaussian mixture model). They determined that there was no major variance in these classifier performances. Moreover, they also recommended that the achievement of more accuracy can be opted for the classification by using three channels optimal EMG signal, if dimensionality reduction and feature sets selection added is significant than the classification method selection and channels are chosen carefully. Scheme et al. in 2011 continued these works where they rated ten classifiers comparable achievement tested [140].

The additional examination on LDA was completed by Khushaba et al. (2012) [141]. They testified an accuracy of ordinary classification of approximately 90% in distinguishing amongst single and combined movements of fingers. They apted EMG of two channels for finger movements from eight participants containing ten individual classes and collective movements of fingers. In distinction to it, set of other studies in classification of movements of hand was completed using both amputee and normal subjects. In this study, the classification precisions differences can be seen as they use EMG of six channels subsequent in fifteen classes of movements of fingers [142].

Both Khushaba et al. in 2012 and Al-Timemy et al. in 2013 could not confirm that whether the accuracy of classification involved in the study was exaggerated by the number of EMG channels or not [141 – 142]. However, the result given by both studies may be limited by the movement class's characteristics and the data usage for training or testing. The classification performances generalization influence by both of these circumstances, and therefore the need to take actions in the contexts of EMG channel, between EMG muscles association, their features and findings drawn based conclusion suitably for this new study is present. It is worth to note that as this type of study is in connection with datasets of big numbers so the window of classification for the set of data (CW) is calculated as below:

$$CW = \frac{x_L - L}{L_{inc}} \tag{3.6.1}$$

Where,

x_L = Size of full dataset.

L = Window length.

L_{inc} = Window size increment.

3.6.1 Artificial Neural Network (ANN)

It is usual to employ multilayer perceptron (MLP) for use in classification of EMG signal and has made reasonable achievement for movement of steady-state classification with promising performances which has been described in numerous research studies [144 – 147].

The algorithms based on biological inspiration are known as artificial neural networks (ANNs) where the information about the problem is dispersed in neurons and their weighted connection. ANNs are based on human brain function mapping formations and are non-linear. They are significant worth for modeling, principally at the association of underlying facts is not explained. Below is the figure 18 that shows basic configuration of ANN and its architecture consisting of three layers: first one is input layer, middle layer is hidden, and third one is layer of output. Moreover, every layer has a bias vector, a weight matrix and a vector output.

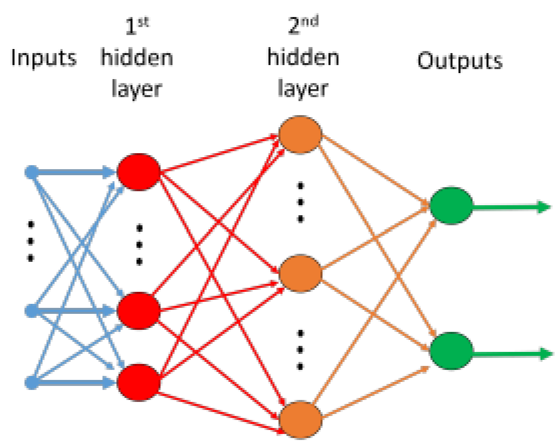

Figure 18 : The ANN basic architecture

3.6.1.1 Back-Propagation Neural Network

The algorithm known for effective system training and its behavior for better understanding is back-propagation neural network (BPNN) classifier algorithm [144, 148 – 150]. The BPNN uses abide by a standard processing systems group which by transmitting signals interacts with each other over huge number of connected weights.

The hyperbolic tangent sigmoid function is used by the algorithm and the applied functions for the hidden and the layers of output are linear. This is finished disconnected for every individual layer. The process of training shall adjust the connected loads and preferences to the desired yield map. The ANN generalization and their procedures achievement is done by modernizing bias values and weights equivalent to the algorithm of Levenberg-Marquardt optimization and applied gradient descent as the purpose of learning [151].

The algorithm of BPNN in basic form can be fixed firstly by preparing the weight standards and level of the network threshold to uniform small distribution of random numbers, the computation particulars for BPNN can be originated in Karlik et al. publication published in 2003 [152]. The BPNN activation functions is recognized as $s_c : \mathrm{R} \rightarrow (0, 1)$ and well-defined by the following equation [153].

$$s_c(x) = \frac{1}{1+ e^{-cx}} \tag{3.6.1.1}$$

Where,

$c =$ constant which should be positive.

The initiation purposes shape differs with respect to the c value.

3.6.2 Linear Discriminant Analysis (LDA)

The broadly utilization of Linear Discriminant Analysis (LDA) is classification of human hand movement based on data of EMG [116, 125, 131, 142]. The LDA purpose is to find a hyper plane that can classify the facts of data unfolding classes of distinct movement of hand. The hyper plane is obtained by investigating for a estimation which displays extreme gap amongst typical classes and decreases within class diversity as assumed that the data is normally distributed.

The multi-class classification details are given by Balakrishnama and Ganapathiraju in 1988 [154] using algorithm of LDA and summarize the procedure as follows:

- Express the dataset of features for training purpose as well as for testing purpose so that it will be classified in the original space.

$$x_1 = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & a_{m3} \end{pmatrix}, x_2 = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ \vdots & \vdots & \vdots \\ b_{m1} & b_{m2} & b_{m3} \end{pmatrix}, \ldots x_i = \begin{pmatrix} i_{11} & i_{12} & i_{13} \\ i_{21} & i_{22} & i_{23} \\ \vdots & \vdots & \vdots \\ i_{m1} & i_{m2} & i_{m3} \end{pmatrix}$$

- The mean computation of every feature set (U_1, U_2, … , U_i) in "i " class. Moreover, the mean of average for the complete input data (x_i).

- The mean computation of universal vector (U) for the complete set of data, approximately for two basic problems of class;

$$U = p_1 \times U_1 + p_2 \times U_2 \tag{3.6.2.1}$$

Whereas, $p1$ and $p2$ are the priory classes probabilities.

- To get the corrected data, subtract the mean from every point of data.

$$x_i^0 = x_i - U \tag{3.6.2.2}$$

- Define the matrix of covariance (cov_i) of the group (i) given by;

$$cov_i = \frac{(x_i^0)^T x_i^0}{n_i} \tag{3.6.2.3}$$

Where,

n_i = Sample class (i) number.

- Calculate the between-group combined covariance matrix provided by

$$P_{cov} = \frac{1}{n_{total}} \sum_{i=1}^{g} n_i cov_i \tag{3.6.2.4}$$

Where,

cov_i	=	Covariance matrix
n_i	=	The number of sample class (i)
n_{total}	=	The entire number of samples for all classes
g	=	Number of classes.

- Calculate the converse of within-group combined $Pcov^{-1}$ matrix.

- Calculate the inverse of between-group combined $Pcov^{-1}$ matrix.

- Employ the rule of discriminant role for a *k* unit given by

$$f_i = U_i cov^{-1} x_k^T - \frac{1}{2} U_i cov^{-1} U_i^T + ln(P_i) \tag{3.6.2.5}$$

Where,

x_k^T	=	The input sample data
P_i	=	Prior probability vector

$$P_i = \frac{n_i}{n_{total}} \tag{3.6.2.7}$$

The numbers of input sample number *k* having extreme f_i are allocated to "i" class. The main notion of LDA is to categorize individuals features conferring to their class of movement in which the priori likelihoods can be maximized. The computational time of LDA is better than ANN, otherwise both performed similarly. The detail discussion of this was done by Tkach et al. in 2010 [96].

3.6.3 Support Vector Machine (SVM)

A binary classifier that practices each class examples as support vectors to produce hyper plane (linear case) which splits classes with the broadest margin is known as SVM classifier. A parameter *C* is specified as it is not always possible to separate classes. It was set to 1 in this work.

SVM was protracted with a scheme of one-versus-all to enable classification of multi-class as it is a binary classifier. This means that for each class a binary classifier was created. All samples are positive samples fitting to that class while others are considered as negative samples. All binary classifiers co-operates when classifying a new test sample to select output class for classifier of multi-class [156].

3.6.4 K-Nearest Neighbor (KNN)

Another classifier is an procedure of K-Nearest Neighbor. It discovers the *K* points of the data trained with the minimum distance of Euclidean to the test model while classifying a new test sample. The test sample then classified by it as the class that contains mostly the neighboring points. The nearest neighbor class is chosen if tied.

3.6.5 Quadratic Discriminant Analysis (QDA)

The regular LDA non-linear form is basically QDA where between classes the covariance matrix may differ. The covariance matrices may be inverted to avoid singularity problems using the pseudo inverse for particular implementation which results in parting of quadratic as in LDA instead of linear. The parameters for QDA were same as used for LDA [157].

3.7 Classification Performance Evaluation

The studied algorithms performance is analyzed by the scheme of ultimate measure of the classification. The classification strategy achievement is assessed by utilizing a non-functional evaluation. The involvement of prosthetic arm is not needed in this technique to evaluate the estimation of classification process achievement in the study. As a result, classification that is accurate based on the class of movement of user and can be used as standard for the performance classification.

3.5.1 Classification Accuracy

One metric is accuracy for evaluating a system of classification. The performance of the classification system is justified by using the computational information and its percentage of correct system classification. The right prediction percentage has been used in many studies and it can be defined as follow:

$$Classification\ Accuracy = \frac{Number\ of\ correct\ predictions}{Total\ number\ of\ predictions}\ X\ 100\% \tag{3.7.1}$$

Accuracy, as for classification of binary might be determined as below based on negative and positive:

$$Accuracy = \frac{TP + TN}{TP+TN+FP+FN} X\ 100\% \qquad (3.7.2)$$

Where,

TP = True Positives

TN = True Negatives

FP = False Positives

FN = False Negatives

In the meantime, for a system of classification, percentage of error can be found as:

$$Error = 100\% - Classification\ Accuracy \qquad (3.7.3)$$

3.7.2 Classification Plot

The results of classification can be shown by using classification plot that utilized time series based trained classifier. The classification plot is an appropriate technique for output classifier analysis which has been discussed by Chan and Green in 2007 [143]. The accurate class together with the class targeted on the y-axis alongside a scale of time in the x-axis is drawn in this graphical plot. The benefit of this type of plot is that it exhibits the distributions error and their time locations.

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CHAPTER 4: RESULTS AND DISCUSSION

The likely combinations from everything in chapter 3 comprise of several values of variables which includes 16 methods of feature extraction, one method of feature reduction and six classifiers. As the main aim of this study is to increase the accuracy of classification as much as possible, PCA is used as a dimension reduction technique. Firstly, all six classifiers were used on extracted features and the accuracy with execution time was measured without applying PCA and results are summarized in table 4.1 and table 4.2. Secondly, these six classifiers were used after applying PCA technique on extracted features and summarized results in table 4.3 and table 4.4 with accuracy and execution time respectively. After correlation of results, it is found which classifier performance is better after applying PCA technique.

A. Dimension Reduction Optimization

The feature reduction becomes obvious while using PCA for classification as certain features is ignored and therefore in the selected features most of the information becomes limited for the entire dataset. Also, this technique of feature reduction once employed leads to change the classification accuracy as it is up to the code written by the programmer and uses reduction of features as is required. Therefore, for calculation of classification accuracy, selected components changes after PCA employment and used SVM, KNN, LDA, QDA, ANN and TREE as a classifiers.

Feature selection	SVM	KNN	LDA	QDA	ANN	TREE
PCA	48.3	70.3	40.9	33.1	56.3	26.2

Table 2 : PCA implemented (in percentage) classification accuracies

Feature selection	SVM	KNN	LDA	QDA	ANN	TREE
	53.9	76.4	30.4	9.1	59.0	46.9

Table 3 : Without PCA implemented (in percentage) classification accuracies

Feature selection	SVM	KNN	LDA	QDA	ANN	TREE
	138.8	88.5	12.1	35.7	273.0	56.3

Table 4 : Execution time (in seconds) of classifiers without PCA implemented

Feature selection	SVM	KNN	LDA	QDA	ANN	TREE
PCA	66.7	40.4	6.0	10.1	150.7	30.5

Table 5 : Execution time (in seconds) of classifiers with PCA implemented

The key goal of this study is to save the information of maximum amount existing in the set of features while reducing the principle components number simultaneously to minimize the cost of computation. It is worth noticing that after applying PCA the execution time decreases while accuracies increase in some classifiers.

B. Train and Test Data Sizes Optimization

To divide a dataset into two proper sets i.e. training and testing data sets plays a very important role in any machine learning step of application-oriented. If the ratio of number of elements in both sets is not proper then it might lead to over-learn or under-learn the system which is unpredicted for improper algorithm learning by the system. Hence, there is optimal division of training and testing data respectively. In this study, one third repetitions of the movements were used approximately to generate test set while to make the training set, residual repetitions were used and noted the accuracy in each case which is already summarized above. In each case, PCA is used for feature reduction and for classification, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Artificial Neural Network (ANN) and Fine Tree (FT) classifiers are used. It was notice in LDA and QDA that there is increase in accuracy at a linear rate as the training data set increases. Hence, for all classification, this proportion was chosen and to make the confusion matrix of the same.

C. Confusion Matrix and Accuracy

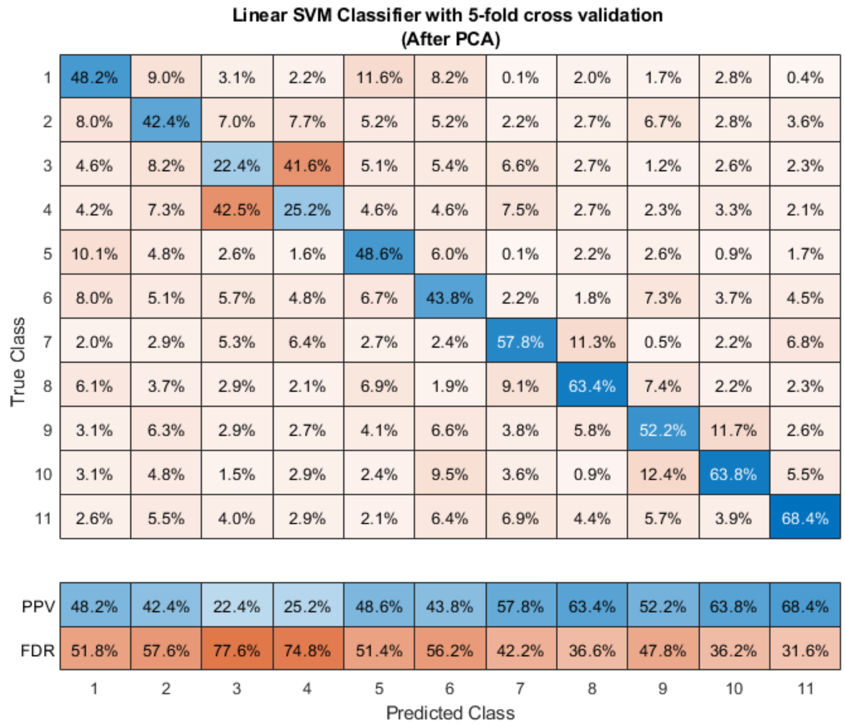
The received data fed into a model after carrying out the cleaning, preprocessing, and disputing to get the output as a probability. But the drawback of this procedure is that the effectiveness of model is not known. The maximum performance of optimization is the requirement which is directly proportional to the effectiveness. So, measurement of effectiveness is a need of this study. To measure the effectiveness, confusion matrix was used as tool.

1. Accuracy

   The classifier correctness measurement after some training is known as accuracy. Different factors like training dataset size, dataset type, classifier type, seeding value, etc. affects accuracy. The accuracy of classification is lower when the complete set of data is taken as features. To cater it 16 features were selected for algorithm along with their moments. From the table 2, KNN looks to provide the maximum accuracy possible.

2. Confusion Matrix Accuracy

   As already discussed, effectiveness measurement of the classification is a requirement and confusion matrix technique is basically a performance measurement for classification of learning of machine. It is like an NXN matrix from its outlook where "N" is number of classes for classified data. The rows of this matrix represent number of data classes in actual and column of this matrix signify number of data classes predicted. Therefore, for any classifier, the matrix should be a diagonal matrix ideally and all the elements being 1 for 100 percent accurate prediction. But, matrix also show the number of classification interpreted incorrectly with their positions as all predictions are not always correct in practice. From the table 4.1 and table 4.2 respectively, it can be seen that twelve types of classifications are done – PCA-SVM, PCA-KNN, PCA-LDA, PCA-QDA, PCA-ANN, PCA-FT, SVM, KNN, LDA, QDA, ANN, FT. The confusion matrix was made for each type. Hence, 12 types of confusion matrix are shown below with 11 classes each. The idea of getting type of error make by the classifier is done by confusion matrix. The accuracy of classification is shown by the color of the boxes.



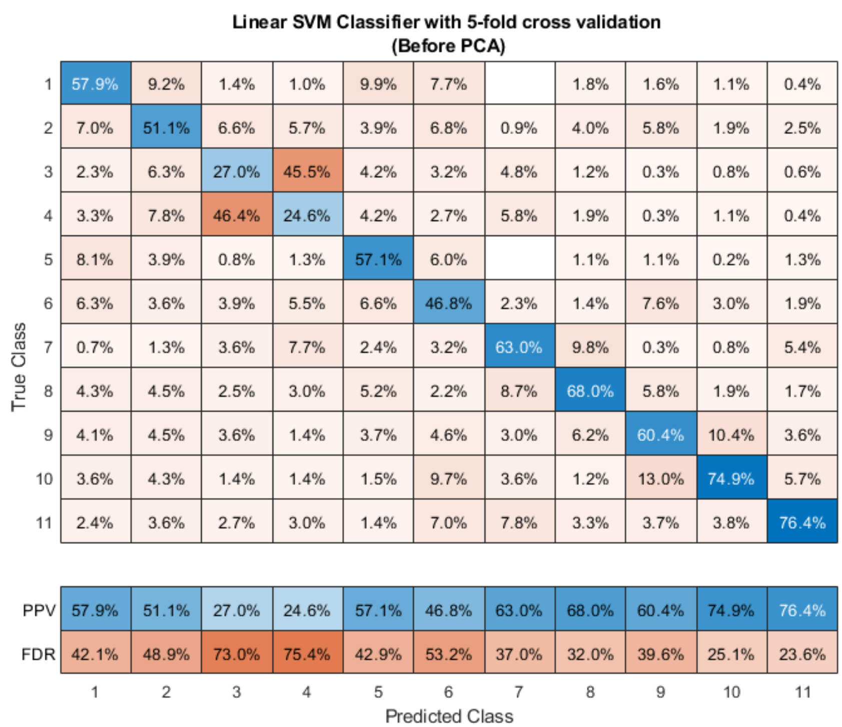
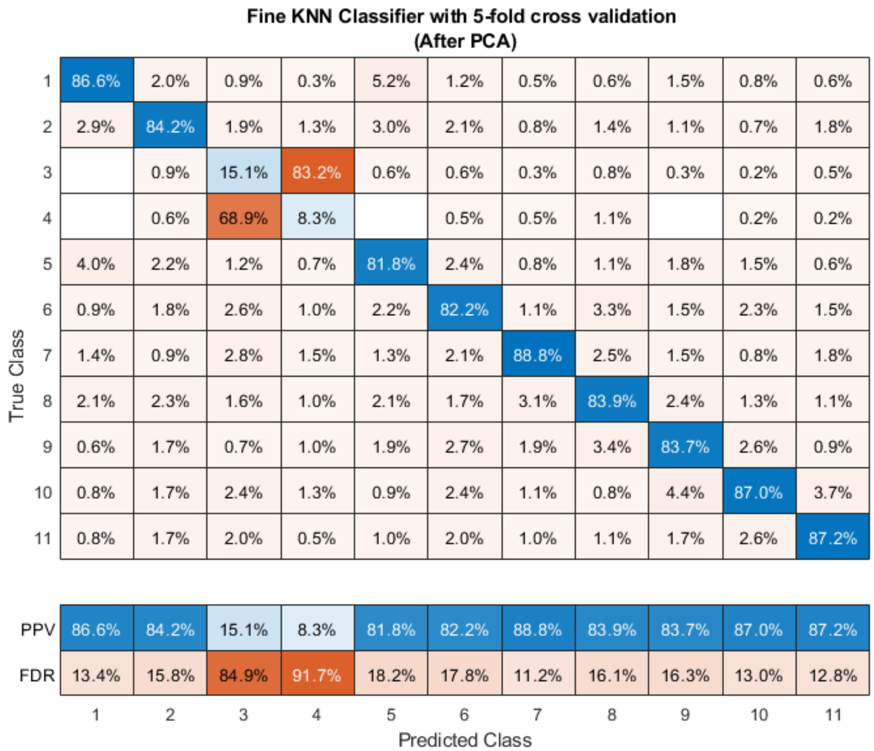
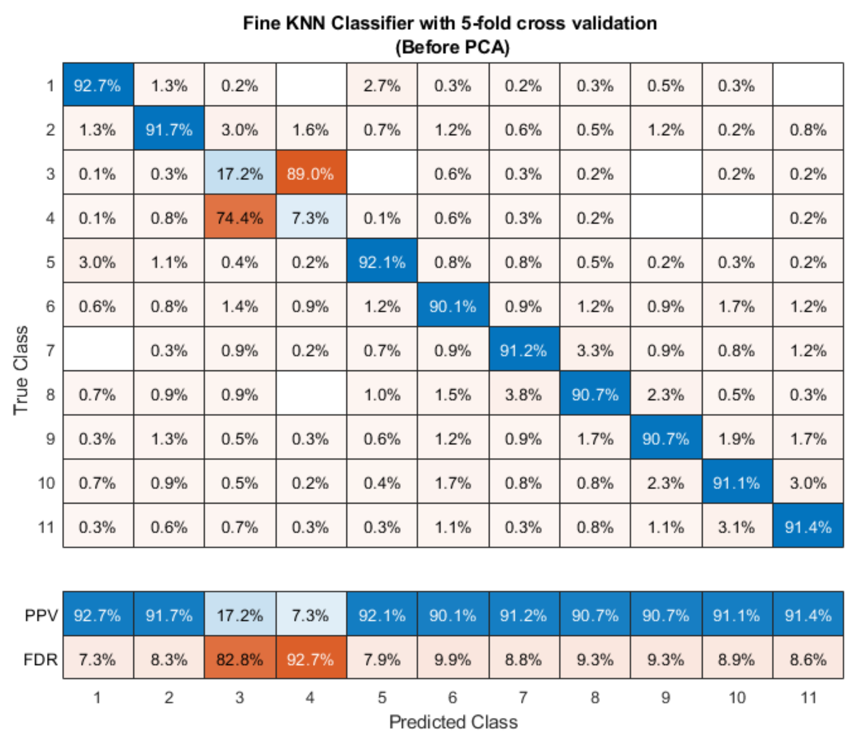
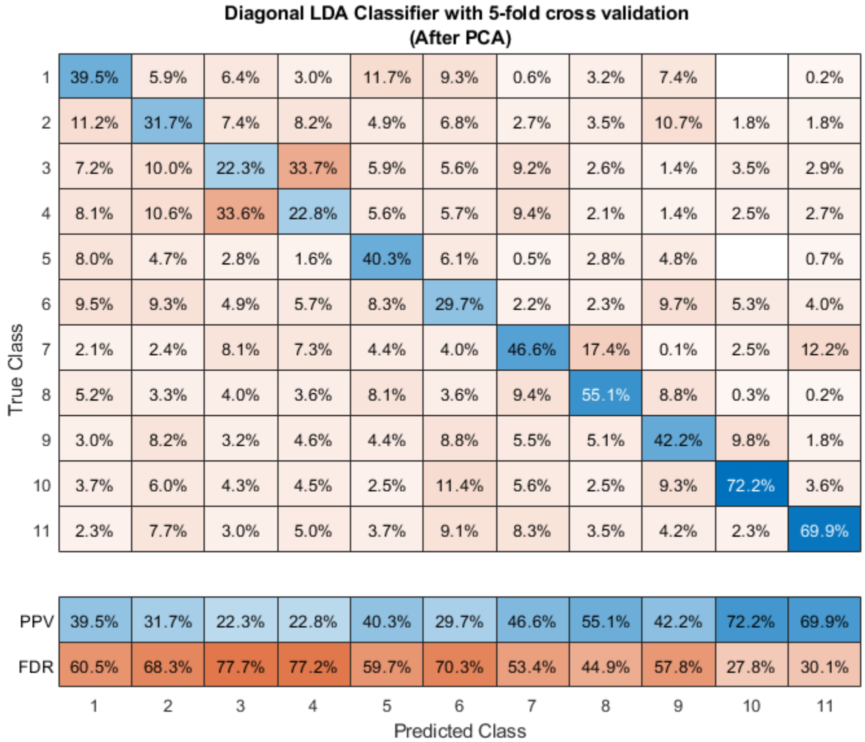


Figure 19 : Confusion matrix of SVM classifier after and before PCA





<u>Figure 20 : Confusion matrix of KNN classifier after and before PCA</u>



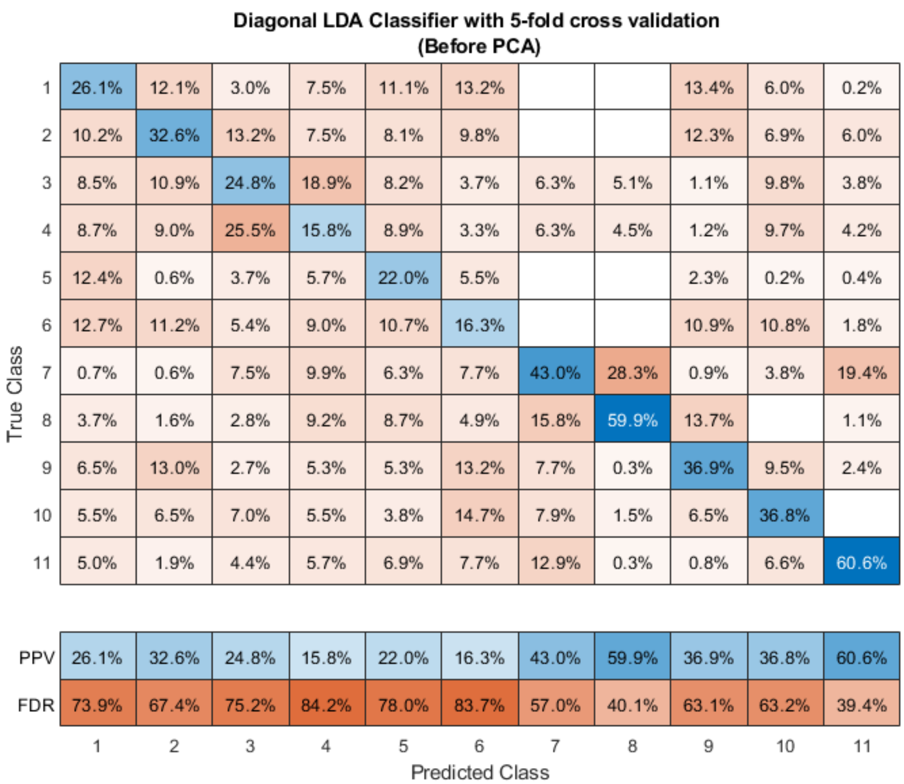
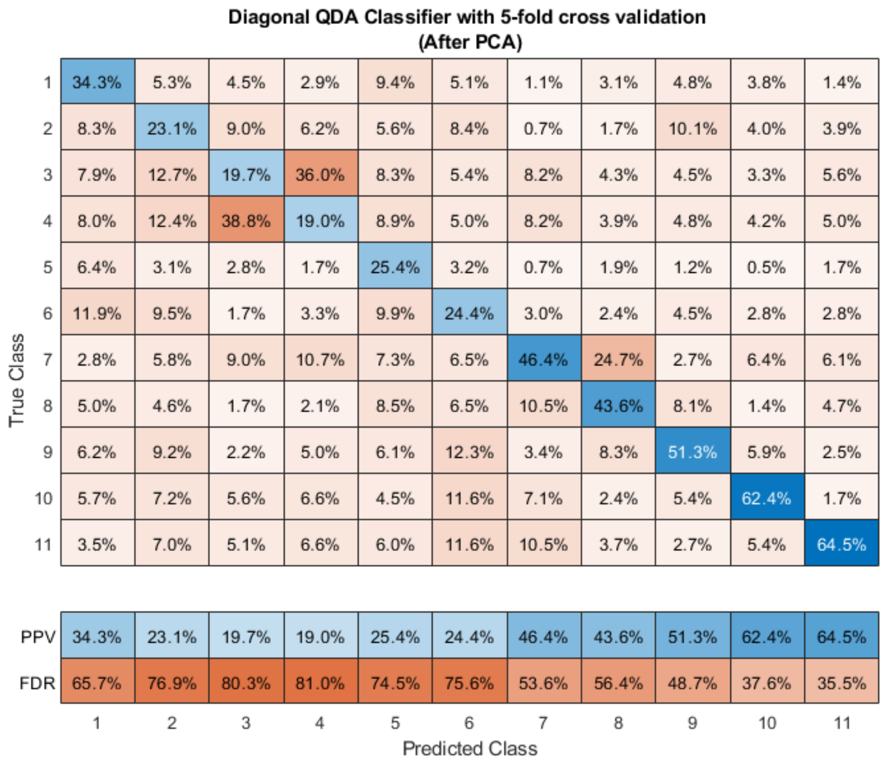


Figure 21 : Confusion matrix of LDA after and before PCA



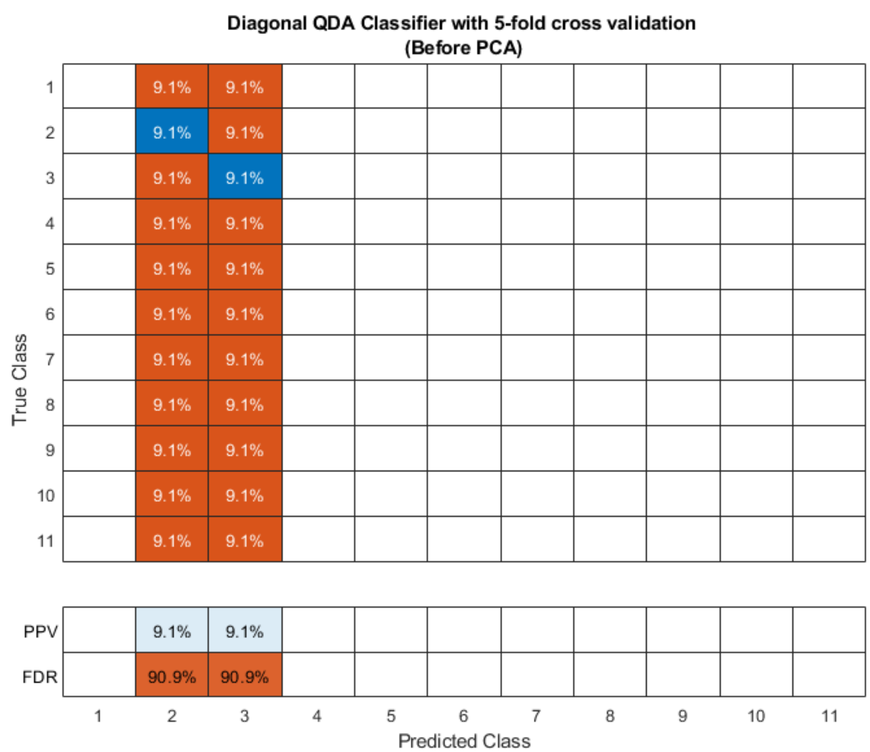
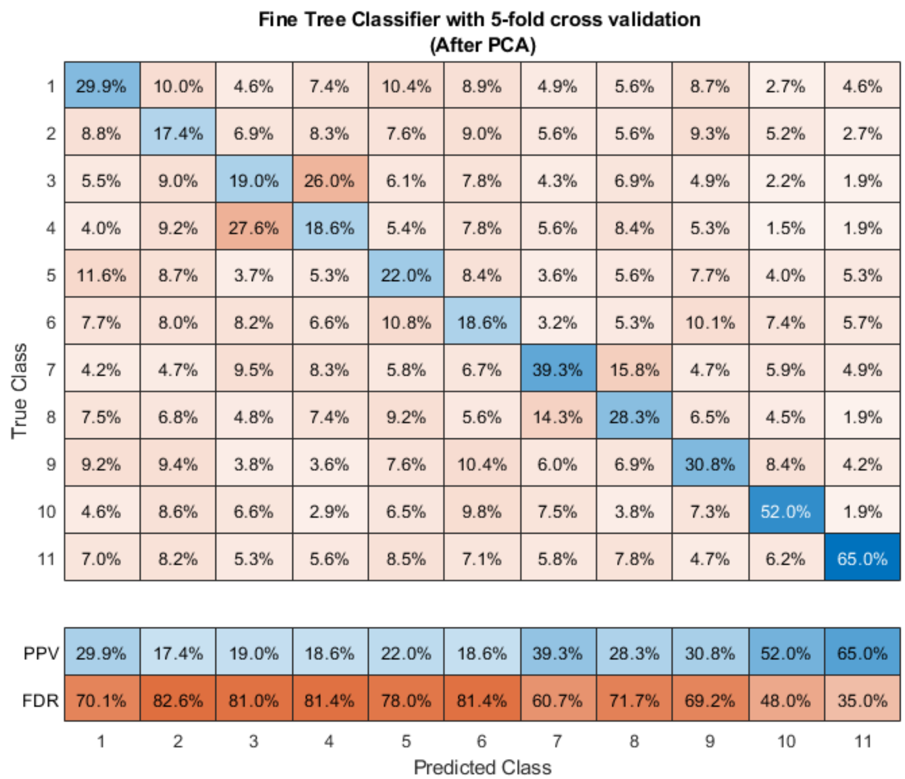


Figure 22 : Confusion matrix of QDA after and before PCA



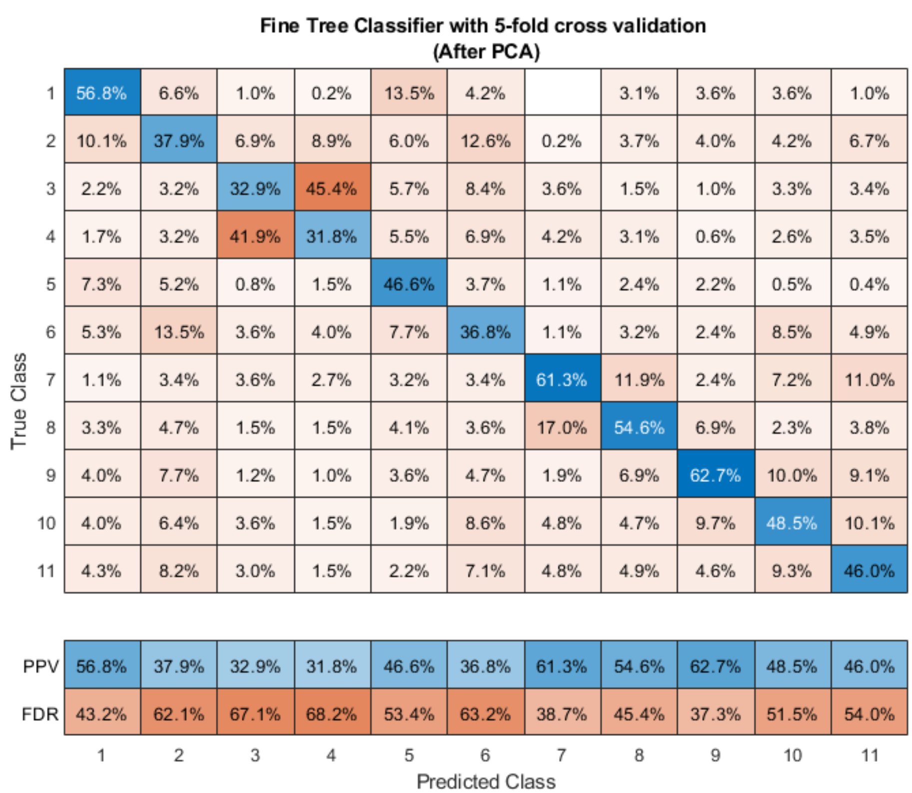
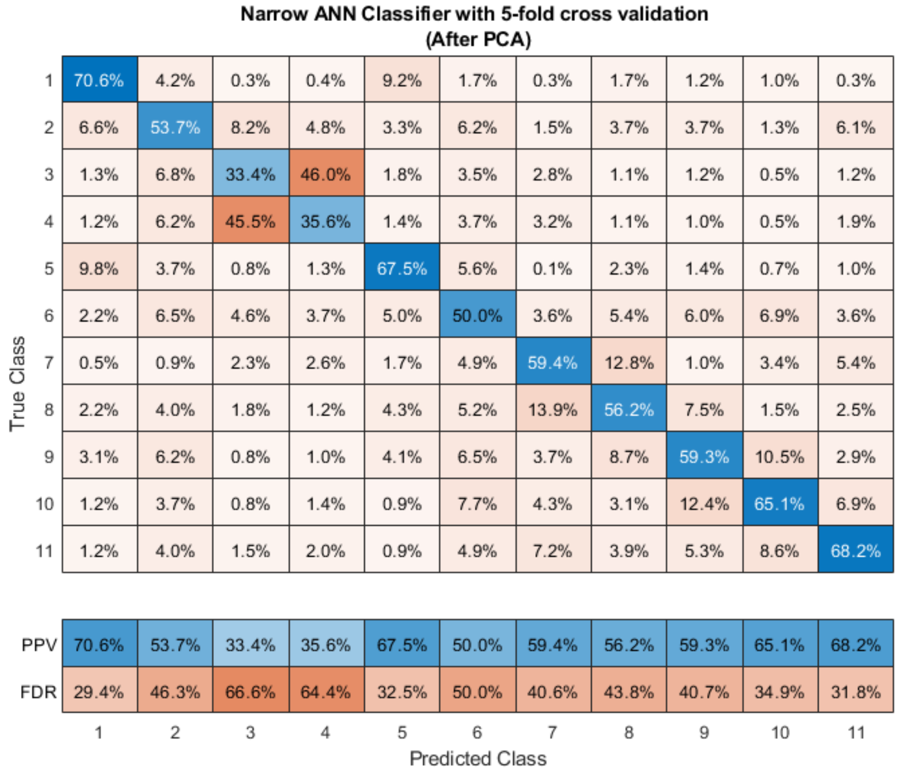


Figure 23 : Confusion matrix of TREE classifier after and before PCA



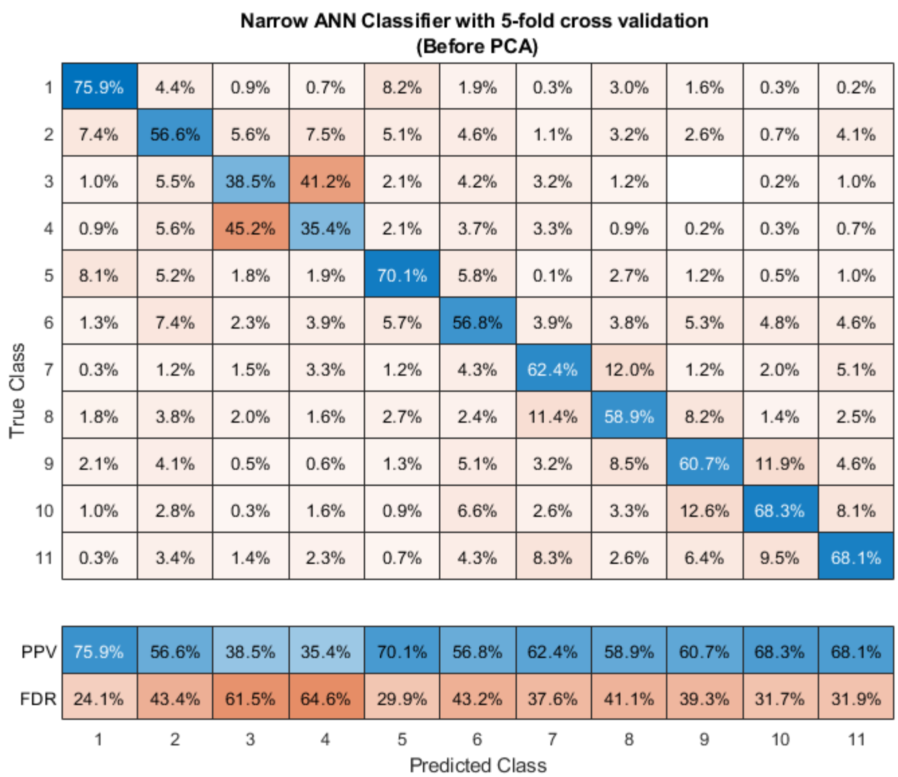


Figure 24 : Confusion matrix of ANN classifier after and before PCA

4.1 Limitations

There are surely some limitations in this thesis as with any studies. Firstly, the study covers only some hand movements and overall muscles were not covered. However, the movements chosen were mostly used in daily routine. Also, because of limited datasets for the analysis of training and testing, there could be variation in classification accuracies if there is increase in number of datasets. Therefore, it is proposed to consider all limits or factors as set up for the use of this technique in the study. Thirdly, pre-processing and classification for the analysis was implemented offline in this study. It is thought that in real time analysis, the functional accomplishment might be not good or lower because of transitions periods possibly between sessions of rest movements. This may affect the classification performance and may results several effects on the characteristics of the EMG signal.

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CHAPTER 5: FUTURE WORK

Like in other research studies, in this thesis too, limited time specifies the end of an effort. It is therefore possible to compute numerous additions and ideas to do more experiments and improve the existing application. The future works suggestions are as follow:

- Usage of real-time or online data to inspect suggested technique from the subject. The online method of performance can be calculated using the recommended offline system. But, the acquired data must be from an extended period to use online records processing to confirm the results reproducibility as many days might be require for reaching. It is therefore a requirement of developing a new online method for the classification act evaluation.

- The proper investigation is a need for transition phases or regions between movements of two states to apply data analysis online. For online purpose, the removed areas are not adequate as used in offline treating.

- For the online classification, the adaptive method has to be windowing system which is thought can reduce the errors of classification. Also, the delay time can be shortening amongst the processing and process of classification by this technique. Therefore, computational cost improves for online recognition.

- In order to observe the success rates, experiments should be conducted with more hand movements of different subjects using the autonomous system of EMG.

- Experiment should be performed with hand amputees to investigate the successful classification rates. This data along with a suitable feature extraction should be processed properly and also be able to give a real application solution for robotic hand control.

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APPENDIX A

Subjects	Classifiers	Before PCA	After PCA
Subject 1	SVM	73.5 %	68.2 %
	KNN	76.8 %	72.4 %
	LDA	52.9 %	66.5 %
	QDA	54.7 %	59.7 %
	ANN	70. 0 %	60.5 %
	FT	58.9 %	40.3 %
Subject 2	SVM	76.4 %	69.8 %
	KNN	79.3 %	71.6 %
	LDA	51.3 %	65.9 %
	QDA	57.1 %	61.5 %
	ANN	73.4 %	64.9 %
	FT	62.4 %	32.4 %
Subject 3	SVM	75.7 %	72.2 %
	KNN	75.4 %	73.6 %
	LDA	52.7 %	68.0 %
	QDA	58.9 %	63.7 %
	ANN	71.1 %	64.3 %
	FT	61.8 %	42.0 %
Subject 4	SVM	67.0 %	60.6 %
	KNN	75.7 %	70.7 %
	LDA	47.8 %	58.7 %
	QDA	49.3 %	50.9 %
	ANN	63.4 %	55.9 %
	FT	55.5 %	31.4 %
Subject 5	SVM	80.5 %	76.1 %
	KNN	79.0 %	74.7 %
	LDA	61.8 %	72.6 %
	QDA	65.8 %	69.2 %
	ANN	76.1 %	67.6 %
	FT	72.5 %	41.9 %
Subject 6	SVM	79.4 %	77.1 %
	KNN	77.6 %	73.9 %
	LDA	62.7 %	72.7 %
	QDA	55.0 %	66.9 %
	ANN	76.7 %	69.7 %
	FT	64.3 %	39.0 %
Subject 7	SVM	77.8 %	74.6 %
	KNN	80.0 %	74.4 %
	LDA	63.6 %	71.9 %
	QDA	66.8 %	68.2 %
	ANN	75.4 %	68.8 %
	FT	65.7 %	44.4 %

Table 6 : Classification accuracies of classifiers before and after implemented PCA

ABBREVIATIONS

EMG	Electromyography
HCI	Human Computer Interface
MCSs	Myoelectric Control Systems
WPT	Wavelet Packet Transform
DWT	Discrete Wavelet Transform
PCA	Principle Component Analysis
SOFM	Self – Organizing Feature Map
LDA	Linear Discriminant Analysis
NLDA	Nonlinear Discriminant Analysis
LD	Linear Discriminant
CNS	Central Nervous System
MUAP	Motor Unit Action Potential
EEG	Electroencephalography
ECG or EKG	Electrocardiography
sEMG	Surface electromyography
iEMG	Intramuscular electromyography
MFAP	Muscle Fiber Action Potential
AP	Action Potentials
MU	Motor Unit
MVC	Maximum Voluntary Contraction
MF	Muscle Fatigue
FD	Frequency Domain

TD	Time Domain
SSC	Slope Sign Change
RMS	Root Mean Square
ZC	Zero Crossing
WL	Waveform Length
AR	Autoregression
MAV	Maximum Amplitude Value
MNF	Mean Frequency
PF	Peak Frequency
MDF	Median Frequency
TFD	Time Frequency Domain
STFT	Short Time Fourier Transform
CWT	Continuous Wavelet Transforms
WVD	Wigner-Ville Distribution
ANN	Artificial Neural Network
K-NN	k Nearest Neighbor
SVM	Support Vector Machine
MLP	Multi-Layer Perception
ELM	Extreme Learning Machine
FIS	Fuzzy Inference System
ANFIS	Adaptive neuro-fuzzy inference system
MCA	Mutual Component Analysis
GA	Genetic Algorithm

NWFE	Non-Parametric Weighted Feature Extraction
FCM	Fuzzy C-Means
SD	Standard Deviation
IAV	Integrated Absolute Value
MAV	Mean Absolute Value
AVR	Average Rectified Value
AAV	Average Absolute Value
NP	Number of Peaks
SM	Spectral Moments
WAVE	Wavelength
WLR	Waveform Length Ratio
MPF	Mean Power Frequency
TP	Total Power
PSD	Power Spectral Density
SM	Spectral Moment
FT	Fourier Transform
WT	Wavelet Transform
PCA	Principle Component Analysis
ULDA	Uncorrelated Linear Discriminant Analysis
BPNN	Back Propagation Neural Network
MLP	Multilayer Perceptron

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