Non Negative Matrix Factorisation for Identification of EMG Finger Movements

A Dissertation submitted towards the partial fulfilment
of the requirement for the award of degree of

Master of Technology
in
Signal Processing & Digital Design

Submitted by

Gaurav Uttam

2K14/SPD/05

Under the supervision of

Dr. Sudipta Majumdar
(Assistant Professor, Department of ECE)

Department of Electronics & Communication Engineering
Delhi Technological University
(Formerly Delhi College of Engineering)
Delhi-110042

JULY 2016

DELHI TECHNOLOGICAL UNIVERSITY

Established by Govt. Of Delhi vide Act 6 of 2009

(Formerly Delhi College of Engineering)

SHAHBAD DAULATPUR, BAWANA ROAD, DELHI-110042

CERTIFICATE

This is to certify that the dissertation entitled **Non Negative Matrix Factorisation for Identification of EMG Finger Movements** submitted by **Mr. Gaurav Uttam, Roll. No. 2K14/SPD/05**, in partial fulfilment for the award of degree of Master of Technology in **Signal Processing and Digital Design (SPDD),** Department of Electronics & Communication Engineering in Delhi Technological University during the year 2014-2016.

Dr. Sudipta Majumdar

Supervisor

Assistant Professor (ECE)

Delhi Technological University

Delhi-110042

DECLARATION

I hereby declare that I have fully cited all materials presented by others which I have used in this thesis. It is being submitted for the degree of Master of Technology in Signal Processing & Digital Design at the Delhi Technological University. The matter presented in this thesis reported has not been submitted by me in any other university/Institute for the award of Master of Technology degree.

Gaurav Uttam

M. Tech. (SPDD)

2K14/SPD/05

Date: October, 2016

Place: Delhi Technological University, Delhi

ACKNOWLEDGEMENT

I owe my gratitude to all the people who have helped me in this dissertation work and who have made my postgraduate college experience one of the most special periods of my life.

Firstly, I would like to express my deepest gratitude to my supervisor **Dr. Sudipta Majumdar**, Assistant Professor (ECE) for her invaluable support, guidance, motivation and encouragement throughout the period during which this work was carried out. I am deeply grateful to **Dr.S.Indu,** H.O.D. (Deptt. Of E.C.E) for her support and encouragement in carrying out this project.

I also wish to express my heart full thanks to all faculties at Department of Electronics & Communication Engineering of Delhi Technological University for their goodwill and support that helped me a lot in successful completion of this project.

Finally, I want to thank my parents, family and friends for always believing in my abilities and showering their invaluable love and support.

Gaurav Uttam

M. Tech. (SPDD)

2K14/SPD/05

Abstract

Electromyography (EMG) signals are becoming important in many applications, including clinical/biomedical, prosthesis or rehabilitation devices, human machine interactions, etc. This work present classification of Surface Electromyography (sEMG) using four different methods, namely, Artificial Neural Network (ANN), Discriminant analysis, Multi-Support Vector Machine (m-SVM) and K-Nearest Neighbour (KNN) method and compares the accuracy of classification of these methods. Also, all the four methods use two methods, namely the nonnegative matrix factorization (NMF) and principal component analysis (PCA) for dimensionality reduction of data. MATLAB simulations show that ANN classifier gives the best accuracy among the four classifier used in this work. The percentage accuracy of ANN classifier is 95% using NMF method and 84.5% using PCA method.

Table of Contents

List of tables

List of figures

Figure 5-12- Result obtained using NMF ………………………………… 37

CHAPTER-1

INTRODUCTION

1.1 Surface Electro MyoGraphy (sEMG)

Surface Electro MyoGraphy (sEMG) is a non-invasive technique for measuring muscle electrical activity that appears during muscle contraction and relaxation cycles. Electromyography is helpful to find a muscle actually does at any moment during movement and postures.

1.1.1 CHARACTERISTICS OF THE EMG SIGNAL

The amplitude of the EMG signal is stochastic (random) in nature and can be represented by a Gaussian distribution function. The amplitude of the signal can range from 0 to 10 mV (peak-to-peak) or 0 to 1.5 mV (rms). The usable energy of the signal is limited to the 0 to 500 Hz frequency range, with the dominant energy being in the 50-150 Hz range.

1.1.2 Detection of sEMG signal

The sEMG signal generated by the muscle fibers is captured by the electrodes, amplified and filtered by the sensors, and then converted to a digital signal by the encoder. It is then sent to the computer to be processed, displayed and recorded by the Infiniti software.

1.1.3 THE ELECTRICAL NOISE

Various types of noise present in sEMG are:-

Electronic noise generated by electronics equipment. This noise has frequency components that range from 0 Hertz to several thousand Hertz (Hz). This noise cannot be eliminated.

Ambient noise originates from sources of electromagnetic radiation, such as radio and television transmission, electrical-power wires, light bulbs, fluorescent lamps, etc.

There are two main sources of motion artifact: one from the interface between the detection surface of the electrode and the skin, the other from movement of the cable connecting the electrode to the amplifier. The electrical signals of both noise sources have most of their energy in the frequency range from 0 to 20 Hz.

The amplitude of the EMG signal is quasi-random in nature. The frequency components between 0 and 20 Hz are unstable because they are affected by the quasi-random nature of the firing rate of the motor units.

1.1.4 Applications:

Surface electromyography is widely used in many applications, such as:

Physical Rehabilitation (physical therapy/physiotherapy, kinesiotherapy and orthopedics)
Urology (treatment of incontinence)
Biomechanics (motion analysis)
Ergonomics (job risk analysis, product design and certification)

1.2 Prosthetic Hand

Human hand is an efficient machine. The organs of the hand play efficient role. It makes the human hand a skillful machine with large number of degree of freedom (DOF). Human hand allows to contact with the environment and to communicate with others and hence, behaves as a complex catalog. The complex movements are performed by synthesizing, so esthetic information from the environment like vibration, pain temperature and most important, touch etc.[1]. In some cases, the person loses their hand either due to some defect, disease, accident or from their birth time. And the loss may be complete or only partial like absence of thumb or any finger. The health related quality of life (HRQL) or quality of life (QoL) evaluates the condition of amputees and it states that elimination is the most different category of HRQL [2]. Such person life can be made normal by using an 'artificial organ' or 'prosthetic hand' in their body. In last few decades, the modern prosthetic hands were designed in such a way to fulfill the requirement of natural limb.
In this work, the EMG signals has been used and classified when, recorded for longer interval of time. Features have been extracted from the EMG signals for better classification and classification accuracy has been calculated.

1.3 Motivation

Robotics is an important area of research now a days. The numerous analytic approaches have been proposed for characterization of grasp and modelling the process of manipulation. In addition, there have been advances in control strategies and tactile sensing for hands. But, still we are a long way from building robots that can independently decide how to operate and mimic naturally. The Otto Bock SUVA (Schweizeirische Unfall Versicherungs Anstalt-Swiss Insurance Agency) hand, is designed so that the grip force is controlled by the intensity of muscle signal. In 1990's researchers found that there is useful information in transient burst of myoelectric signal [5]. This requires discrimination of patterns and classifying the features accurately extracted from the signal.

1.4 Objective

The challenge in pattern recognition for developing a human computer interaction system and the hand prosthesis are feature evaluation and the classification of signals. This work uses different classification methods based on muscle synergy and compare them. These methods are also used for developing the prosthetic hand.

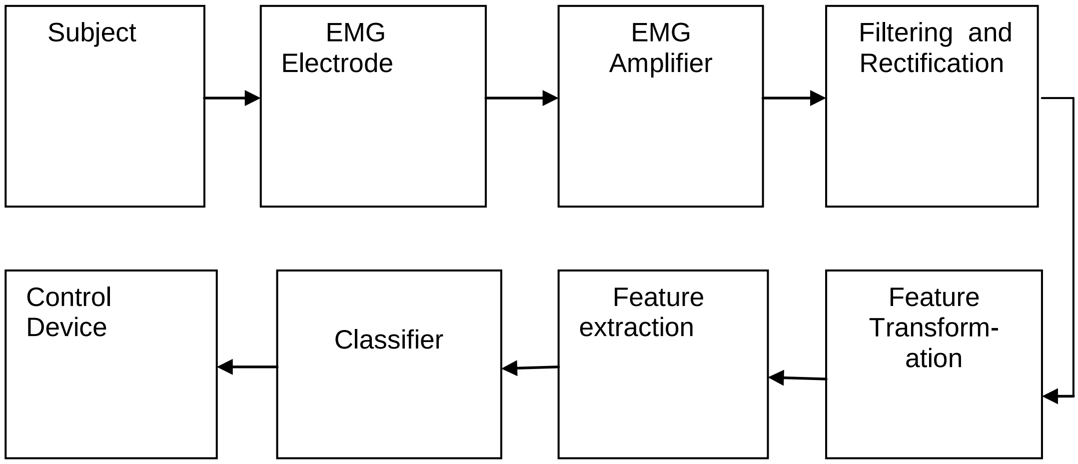


Fig. 1.1 General scheme of EMG classification

The common finger movements are divided into two main categories namely, simple and complex movements.

- Simple movements are further categorized as :-
  1. Thumb (T)
  2. Index finger (I)
  3. Middle finger (M)
  4. Ring finger (R)
  5. Little finger (L)
- Complex movements are categorized as :-
  1. Thumb-index (TI)
  2. Thumb-middle (TM)
  3. Thumb-ring(TR)
  4. Thumb-little(TL)
  5. Hand close (HC)

The factors that affect the recognition of movement using facial EMG are:- inter-subject and intra-subject performing style, performing speed and force difference during multitask etc.

1.5 Applied Method

The present work begins with a survey of EMG signal processing techniques and applications, which consists of finding better classification schemes for EMG signal processing applications in prosthesis hand control. The electromyographic datasets (EMG) have been taken and feature extractions, dimension reduction (using non-negative matrix factorization and principal component) have been implemented. Further, classification using artificial neural network (ANN), support vector machine (SVM) and discriminant method has been done and classification accuracy has been compared.

1.6 Thesis Organization

The organization of this thesis is structured as follows:

Chapter 1 gives the introduction to the Human Computer Interaction. It also explains the use of EMG based hand prosthesis technique and objectives.

Chapter 2 gives the brief description of the electromyography techniques (EMG), which provides the early and recent developments in the field of EMG technique, its processing and applications.

Chapter 3 presents processing techniques used in this thesis.

Chapter 4 presents the feature extraction and classification of EMG signals.

Chapter 5 presents implementation and simulation results.

Chapter 6 presents the conclusion and the future scope of the work.

CHAPTER-2

LITERATURE REVIEW

EMG technique for prosthetics is a promising method in the field of biomedical and robotics engineering. Different methods have been used for this purpose. Shyu Liang-Yu el al. [3] in 2002, gave a new electrode system namely, AGCL electrodes for hand action discrimination. Transducers were used to convert the bio signals to some process able electrical signal. The authors achieved this by using three methods of gathering signals via. Ag/Agcl, Ag, Au electrodes.

1) Invasive (needle) electrode
2) Non-invasive (surface) electrode
3) Radio transmitter

Third one is the radio transmitter, which is difficult to use as it is to be planted inside the muscle.

In 2005, Yonghong Huang [4] evaluated usage of Gaussian mixture models (GMMs) for multiple limb motion classification and for continuous myoelectric signals. A complex experimental calculation was demonstrated on 12 subject database. The experiments evaluated the GMMs algorithmic including the model order selection and variance limiting, the segmentation of the data, and various feature sets including, time-domain features and autoregressive features. The post-processing of end results using a majority vote rule were used. This paper also presents the comparison of performance of the GMM with the commonly used classifiers, namely linear discriminant analysis, a linear perceptron network, and a multilayer perceptron neural network. The GMM-based limb motion classification system presented outstanding classification accuracy and resulted in a healthy method of motion classification with low computational load. Hongbo Xie presented excellent results of EMG classification and feature extraction using neural network classifier and time and frequency domain method of feature extraction. Also, Richard T. Lauer implemented an adaptive neuro-fuzzy inference system (ANFIS) with a supervisory control system (SCS) to forecast the incident of gait events using the electromyography (EMG) actions of lower extremity muscles in the child with cerebral palsy (CP). The accuracy in predicting gait events ranged from 98.6% to 95.3%.

In 2007, Rami N. Khushaba [6] presented a modern approach to decrease the computational cost of real time systems driven by Myoelectric signals (MES). For the feature extraction process of the subsets, Particle Swarm Optimization (PSO) was used. Further, evaluation of these subsets was done using a multilayer perceptron trained with back propagation neural network (BPNN). The result showed that the smallest error rates can be obtained by considering the correct combination of features/channels, thus providing a feasible system for sensible functioning purpose for rehabilitation of patients.

In 2009, Rami N. Khushaba [6] proposed a fuzzy discriminant analysis feature projection technique for myoelectric control. The presented a novel feature projection technique based on a combination of fisher linear discriminant analysis (LDA), fuzzy logic (FL), and differential evolution (DE) optimization technique. An advanced technique DEFLDA, gave different membership degrees to the data points, so as to maintain low effect of overlapping points in the discrimination process.

In 2013, Keehoon Kim [7] have used a haptic feedback to improve grip force control of surface electromyography (sEMG). The proposed paper calculates the hypothesis via an sEMG-controlled virtual prosthetic arm operated by targeted reinnervation (TR) amputees under diverse haptic feedback conditions. [8] used an supervised feature projection based EMG pattern recognition method for hand movement. [9] presented EMG signal analysis using wavelet transform.

In 2015, Ganesh R. Naik [10] have presented the concept of muscle synergy and utilized non-negative matrix factorization as a dimension reduction technique. This paper also used Artificial Neural Network (ANN) classification scheme to control finger movements and result shows 92% and 84% classification accuracy for simple and complex finger.

In 2016, Vincent Carriou et al. [11], have proposed a fast generation model of high density surface EMG signals in a cylindrical conductor volume. In [12], D. Johansen proposed the feasibility of using an inductive tongue control system (ITCS) for controlling robotic/prosthetic hands and arms and a dual modal control scheme for multi-grasp robotic hands combining standard EMG with the ITCS. The results showed that ITCS control scheme is 1.15 seconds faster than the EMG control scheme, corresponding to a 35.4 % reduction in the activation time. The largest difference is for grasp 5 with a mean AT reduction of 45.3 % (2.38 s). In [13], Adenike A. Adewuyi et al. have proposed pattern recognition control scheme in surface electromyography (EMG) for the extrinsic hand muscles.

CHAPTER 3

METHODLGY

3.1 Introduction

The whole concept of the work can be summarized in few steps shown in Fig. 3.1

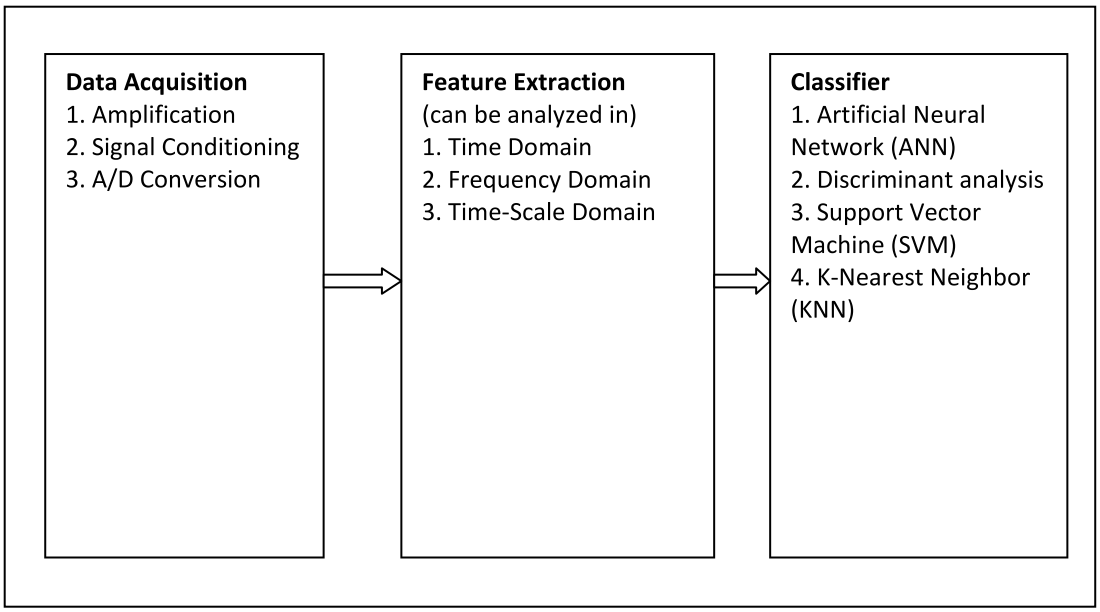


Fig. 3.1 Stages of SEMG signal processing

The five major components of pattern recognition are:

1) Experimental Setting
2) Sensing
3) Preprocessing
4) Feature Extraction
5) Classification

3.2 Signal Processing Techniques

The processing of sEMG signals can be divided into three stages. The first stage consists of data acquisition that includes amplification, analogue to digital conversion and signal conditioning. Second stage is a signal processing stage to extract desired features from the bio-signal. Third stage is a feature selection stage, which retains important information for the later application such as classification of signals using an Artificial Neural Network (ANN).

3.2.1 Data Acquisition

A signal is detected at the intended biological site by using surface electrodes as sensors. Theses electrodes also provide an interface between electrical recording device and the biological system. After detecting the signal by electrodes, it is usually amplified, filtered and converted to a digital signal. Signal amplification is also required, as muscle signal is usually weak and is in the microvolt range. Since the sEMG signals are small, measurement is subjected to interference from electrical equipment, such as movement of cable carrying signals from the body to the measuring instrument. A band-pass filter is used at the electrode site to remove interferences, which effectively cancels the ambient electrical noise.

3.2.2 Feature Extraction and Selection

Large number of inputs and randomness of the signal, make signal impractical to direct classification. Therefore, the sequence must be mapped into a smaller dimension vector, called a feature vector. Extracted information from EMG signals are represented by a feature vector to minimize the control error. Features represent raw myo-electric signals for classification, therefore, selection and extraction of features is needed. A large number of features has been introduced in the literature for myo-electric classification. Features fall into one of three domains: time, frequency and time-scale.

3.2.2.1 Time Domain

Common procedures are used to detect muscle activation. These are described by the observable lobes appearing in the sEMG time series. Different types of digital operations can be performed to obtain the desired information. They are:-

1. **Full-wave Rectification** The full wave rectification is defined as

$$SEMG_{rec}(i) = |SEMG(i)| \tag{3.1}$$

Where, SEMG(i) is the i^{th} sample of the discrete SEMG signal.

2. Root Mean Square

This is used to calculate the amplitude of the SEMG. Therefore it is a force indicator. It is defined by:

$$RMS = \sqrt{\frac{\sum_{I=0}^{n} A_i^2}{N}} \qquad (3.2)$$

Where, *A* is amplitude in *i*th sample and N is total number of samples.

3. Mean Absolute Value

This is an estimate of the mean absolute value (MAV) of the signal in the segment *i* having N samples in length.

$$\bar{X}_i = \frac{1}{N}\sum_{i=1}^{N} |x_i| \qquad (3.3)$$

4. Wilson Amplitude

This is the number of counts for each change of the sEMG signal amplitude that exceed a predefined threshold. It is given by:

$$WAMP = \sum_{i=1}^{N} f(|x_i - x_{i-1}|) \qquad (3.4)$$

Where, f(x) = 1 if x>threshold, 0 otherwise. This unit is an indicator of firing of motor unit action potentials (MUAP) and, therefore, an indication of muscle contraction level.

5. Variance

The variance is a measure of the signal power and is calculated as:

$$VAR = \frac{1}{N-1}\sum_{i-1}^{N} x_i^2 \qquad (3.5)$$

6. Waveform Length

This is the cumulative length of the waveform over the time segment. It is defined as

$$I_0 = \sum_{i-0}^{N} |\Delta X_i| \qquad (3.6)$$

This parameter gives a measure of waveform amplitude, frequency and duration all, in one.

7. Autoregressive Coefficients

Using an autoregressive (AR) model, new samples are represented as linear combination of past samples. The model can be represented as:

$$\hat{y}_i = \sum_{k=1}^{M} a(k)y(i-k) + w(i) \qquad (3.7)$$

Where, y is the sEMG signal, a(k) is the coefficients of the model, w(i) is a random white noise and M is the order of the model. M=4 is suitable for EMG signals.

3.2.2.2 Frequency Domain

Spectral (frequency domain) analysis is mostly used to study muscle fatigue. It is commonly used in applications where oscillators or repetitive patterns are involved, for instance in the case of motor unit (MU) activation and pathological tremor. Power spectral density (PSD) plays a major role in spectral analysis. In wide-sense stationary stochastic signals, PSD is defined as the Fourier transform of the autocorrelation function of a signal. Its two characteristic variables, the mean and median frequency, provide some basic information about signal spectrum and its change over time. Fourier analysis is a mathematical technique for transforming a signal from time domain to frequency domain by breaking down a signal into constituent sinusoids of different frequencies. Fourier transform is a generalization of the Fourier series, where function is represented by the sum of sines and cosines. Fourier transform uses exponentials and complex numbers.

The Fourier transform of input signal x(t) is defined as:

$$F(w) = \int_{-\infty}^{W} x(t)e^{-jwt} \qquad (3.8)$$

Where, ω is the angular frequency, ω= 2Πf, f is the input frequency, x(t) is the time domain signal and F(ω) is its Fourier transform represented in frequency domain.

1. Mean Frequency

Fatigue is related to the frequency of motor unit (MU) activation. The evolution of the mean frequency is used as a fatigue index. It is defined as:

$$\bar{F} = \frac{\sum_{i=0}^{n} f_i A_i^2}{\sum_{i=0}^{n} A_i^2} \qquad (3.9)$$

where *F* is mean frequency, f_i is frequency in i^{th} sample, *i A* is amplitude in *i*th sample and *n* is total number of samples.

2. Median Frequency

This is another parameter that can be used to assess muscle fatigue. The median frequency is given by the frequency that divides the power spectrum into two regions containing the same amount of power. The median frequency is the frequency having 50% or half of the frequency distribution on each side.

3.2.2.3 Time-Scale Domain

Fast Fourier Transforms (FFTs) are most commonly used to determine the frequency spectrum of the sEMG signal. It has drawbacks. In transforming to the frequency domain, time information is lost. Another Fourier Transform, Short Time Fourier Transform (STFT), is a form to solve the FFT drawback and maps a signal into time and frequency functions. FFT provides information about which frequencies are present in a signal. However, as STFT is using a window to analyze a signal, the information is therefore obtained with limited precision determined by the size of the window. Thus, narrow window has good time resolution, but poor frequency resolution; while, large window has poor time resolution, but good frequency resolution. Besides, another drawback of STFT is assuming the signal is stationary within the window size, therefore it is not suitable to be used for non-stationary sEMG signal. Also, it has fixed time frequency resolution.

The varying time frequency resolution can be obtained using continuous as well as discrete forms of wavelet transforms. The continuous wavelet transform was developed as an alternative approach to the Short Time Fourier Transform (STFT), to overcome the resolution problem. The wavelet analysis is done in a similar way to the STFT analysis, in the sense that the signal is multiplied with a function and the transform is computed separately for different segments of the time domain signal.

$$CWT_x^{\psi}(\tau, s) = \Psi_x^{\psi}(\tau, s) = \frac{1}{\sqrt{|s|}} \int x(t) \psi^* \left(\frac{t-\tau}{s}\right) dt \qquad (3.10)$$

From the above equation, the transformed signal is a function of two variables, τ and s, the translation and scale parameters, respectively. ψ(t) is the transforming function, and it is called the mother wavelet. The continuous wavelet transform is computed by changing the scale of the analysis window, shifting/translating the window in time, multiplying by the signal, and integrating over all times. In the discrete case, filters of different cutoff frequencies are used to analyze the signal at different scales. The analysis of the signal at different resolutions is obtained by expanding and compressing the wavelet.

$$x[n] * h[n] = \sum_{k=-\infty}^{\infty} x[k].h[n-k] \qquad (3.11)$$

The wavelet decomposition corresponds to passing of a signal through filters successively and by dividing the signal into detailed coefficients and approximation coefficients. At every level of decomposition, the data is filtered and then the approximation and detailed coefficients are produced from this filtered data. The same process is followed for further levels of decomposition. Suppose we have a signal S, after the decomposition, we get A_1 Approximation coefficient and D_1 detailed coefficient. If we do the decomposition of the A_1 then we get AA_2 and DA_2 as the approximation and detailed coefficients of A_1. The same procedure is followed for D_1 and so on. In this way, a decomposition tree can be obtained for any number of decomposition levels, as shown in Fig. 3.2.

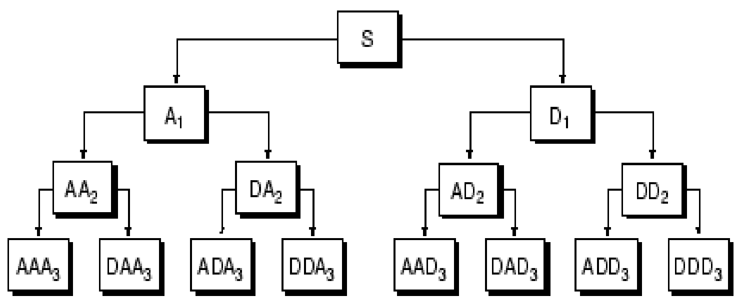


Fig.3.2 The Wavelet Decomposition Tree.

WT is an efficient mathematical tool for local analysis of non-stationary signals, that uses timescale region to analyse a signal as shown in Fig.3.3. It provides a flexible time-frequency resolution without disobeying the Heisenberg uncertainty principle, unlike STFT, which has constant time frequency resolution.

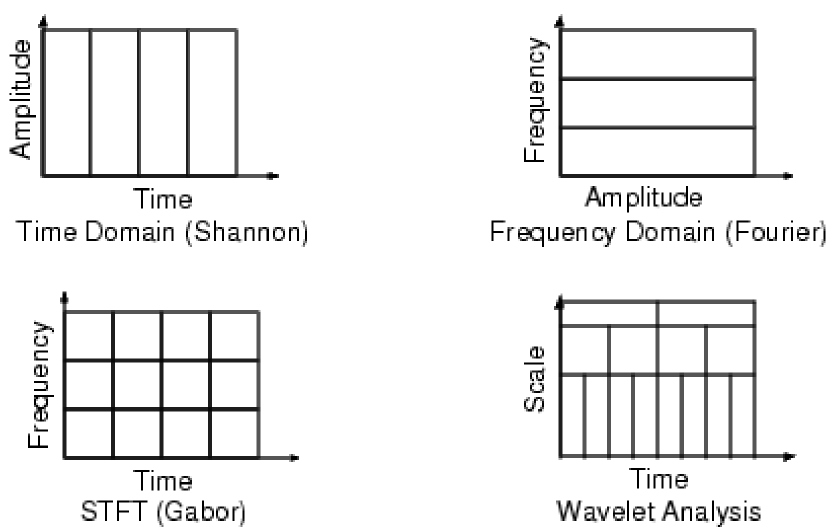


Fig.3.3 Different domains of signal analysis

The wavelet family consists of scaled and time shifted version of single function, called mother wavelet, Ψ (t) , given by

$$\Psi_{a,\tau}(t) = \frac{1}{\sqrt{a}}\left(\frac{t-\tau}{a}\right) \tag{3.12}$$

When ‘a’ becomes large, the basic function Ψaτ becomes a stretched version of the prototype, which represents the low frequency components. A small ‘a’ contracts the basic function $\Psi_{a,\tau}$ and stresses the high frequency components.

Mean absolute value (MAV) and root mean square (RMS) are two well-known time domain features. Theoretically, when a signal is modeled as a Gaussian random process, RMS provides the maximum probability estimation of amplitude in a constant force and non-fatiguing contraction. RMS is the better fit at high level of contraction and MAV is well fit for low contractions and fatigued muscle.

STFT (frequency domain) and DWT (time-scale domain) techniques have also been widely used to extract raw sEMG signal features and import to neural network to classify six output patterns. Few of the features are calculated using the standard equations as follows

$$\text{Energy,}\quad \mathrm{ED_i} = \sum_{k=1}^{N} |\mathrm{C_{ik}}|^2 \qquad i = 1, 2, \dots, l. \tag{3.13}$$

$$\text{Standard Deviation,}\ \sigma_i = \frac{1}{N-1}\sum_{k=1}^{N} (\mathrm{C_{ik}} - \mu_i)^2, \quad i = 1, 2, \dots, l. \tag{3.14}$$

$$\text{Mean,}\ \mu_i = \frac{1}{N}\sum_{k=1}^{N} C_{ik}, \quad i = 1, 2, \dots, l. \tag{3.15}$$

$$\text{Kurtosis,}\ KUR_i = \frac{E(C_{ik}-\mu_i)^4}{{\sigma_i}^4}, \quad i = 1, 2, \dots, l. \tag{3.16}$$

$$\text{Skewness,}\ SK_i = \frac{E(C_{ik}-\mu_i)^3}{{\sigma_i}^3}, \quad i = 1, 2, \dots, l. \tag{3.17}$$

$$\text{Entropy,}\quad EN_i = -\sum_{k=1}^{N} C_{ik}^2 Log(C_{ik}^2), \quad i = 1, 2, \dots, l. \tag{3.18}$$

$$\text{Median,}\ med_i = \sum_{k=1}^{N} \mathrm{median}(\mathrm{C_{ik}}),\ i = 1, 2, \dots, l. \tag{3.19}$$

3.3 Pattern Recognition

The pattern recognition is concerned with the automatic discovery of regularities in data through the use of computer algorithms and to classify the data into different categories. Pattern recognition aims to classify data or patterns based either on *a* priori knowledge or on statistical information extracted from the patterns. The patterns to be classified are usually groups of measurements or observations, defining points in an appropriate multi-dimensional space. This is in contrast to pattern matching, where the pattern is rigidly specified. Many researchers have used different techniques to recognize EMG, such as artificial neural networks (ANN), fuzzy logics (FL) and adaptive neuro-fuzzy inference system (ANFIS).

3.3.1 Artificial Neural Network(ANN)

ANN systems are simplified mathematical models of the brain-like systems that function as parallel distributed computing networks which can be trained to learn new associations, functional dependencies and new patterns. ANNs are adaptive, that is they can automatically adjust to modify their behavior in response to nonlinear dynamics of their environment [14].

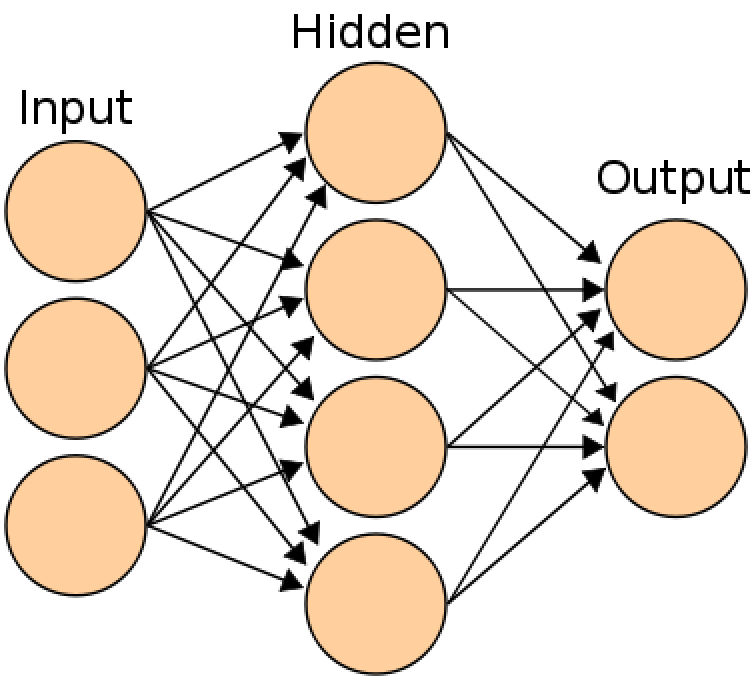


Fig.3.4 Artificial Neural Network

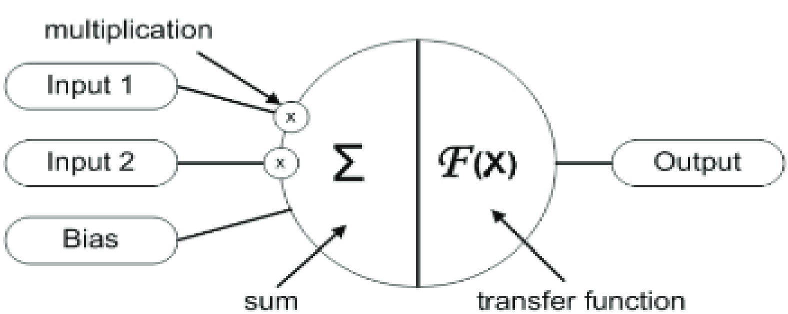


Fig 3.5 Neural Network

Following equation explain the above given Neural Network

$$y(k) = F(\sum_{i=0}^{m} w_i(k).x_i(k) + b)$$

Where

y(k)= output

w(k)= weight

x(k)=inputs

b= bias and F is a activation function

3.3.2 Support Vector Machine

The foundations of Support Vector Machine (SVM) were originally laid in 1963 by Vladimir N. Vapnik.. Thereafter, a few publications formed milestones in the journey of SVM. In 1992, another publication by Bernhard E. Boser, Isabelle M. Guyon and Vladimir N. Vapnik paved the way for the present day SVM. In 1995, Vapnik et al. presented the support vector networks, forming the todays SVM.

SVM has high generalization. Fig. 3.6 shows the hyperplane, support vectors and optimal margins. The architecture of an SVM has data sets {(x_1,y_1), . . ., (x_m,y_m)}, have x patterns of the data with y class labels of each data set x. In the present work, two labels–epileptic and non-epileptic–designated by +1 and -1 are used. The classes are presented with each data to the SVM during training. The SVM tries to construct the optimal hyperplane yielding the maximum margin of separation between the members of the two classes by solving the following quadratic programming optimization problem. A soft margin can be constructed by introducing a slack variable β_i, i = 1, . . ., m, where m is the number of samples. The optimization problem becomes:

$$\underset{(W,b,\beta i)}{Minimize} \quad \frac{1}{2}||W||^2 + D\sum_{i=1}^{m}\beta_i \tag{3.20}$$

Subject to $y_i\big((W * X_i) + b\big) \geq 1 - \beta_i$, D>0.

$\beta_i \geq 0, \quad i = 1, 2, \dots, m$

$$W \in R^N,\ b \in \Re.$$

D is a user-defined constant greater than zero. This problem can be simplified by its Lagrangian dual as follows:

$$\underset{(a \in \Re^n)}{Minimize} \quad \sum_{i=1}^{m} a_i a_j y_i y_j (X_i X_j) \tag{3.21}$$

With $D \geq a_i \geq 0$

$$\sum_{i=1}^{m} a_i y_i = 0$$

$$Here\ W = \sum_{i=1}^{m} a_i y_i X_i$$

i=1, 2, … , m.

The decision function becomes

$$f(x) = \sum_{i=1}^{m} (a_i y_i (X.X_i) + b) \quad (3.22)$$

From this deduction, the patterns X_i ($a_i \neq 0$) are the support vectors. These support vectors lie on the margin of the decision boundary and all other data points are irrelevant. The feature vector X only appears in the equations as dot products, so, the decision functions can be written as

$$f(x) = \sum_{i=1}^{m} (a_i y_i K(X.X_i) + b) \quad (3.23)$$

Where $K(X.X_i)$ is kernel function and is simply the dot product of X and X_i . The linear function is used in the present application. Other types of kernel functions can

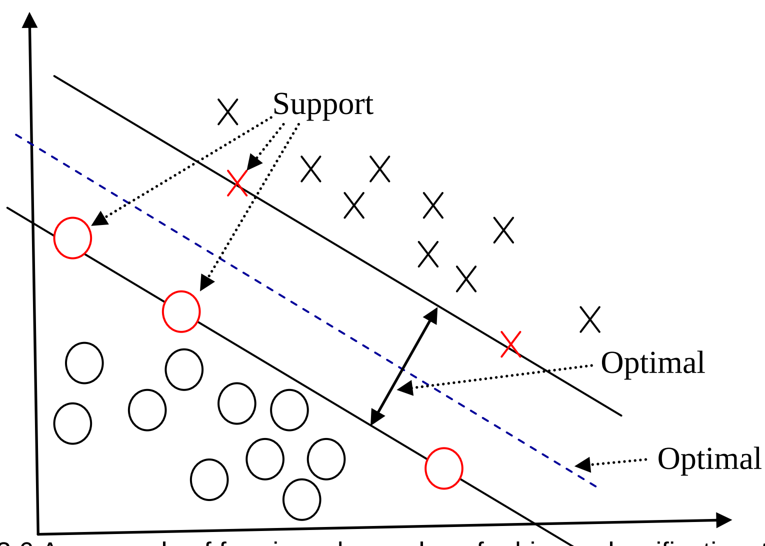


Fig. 3.6 An example of forming a hyperplane for binary classification, the cross and round marks in red are support vectors.

3.4 Algorithms of Pattern Recognition

3.4.1 Principle Component Analysis

Principal component analysis (PCA) is a useful statistical technique which is widely used in different fields such as face recognition and image compression. It is a common technique for finding patterns in data of high dimensions. It is a simple method of extracting relevant data from large data.

PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables.

This transformation is defined in such a way that the first principal component has the largest possible variance (that is, accounts for as much of the variability in the data as possible), and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to (i.e., uncorrelated with) the preceding components. The principal components are orthogonal because they are the eigenvectors of the covariance matrix, which is symmetric.

PCA allows us to compute a linear transformation that maps data from a high dimensional space to a lower dimensional sub-space.

$$b_1 = t_{11}a_1 + t_{12}a_2 + \cdots + t_{1n}a_N$$

$$b_2 = t_{21}a_1 + t_{22}a_2 + \cdots + t_{2n}a_N$$

....

$$b_k = t_{k1}a_1 + t_{k2}a_2 + \cdots + t_{kn}a_N$$

or y=Tx

where

$$T=\begin{bmatrix} t_{11} & t_{12} \cdots & t_{1N} \\ t_{21} & t_{22} \cdots & t_{2N} \\ t_{k1} & t_{k2} \cdots & t_{kN} \end{bmatrix}$$

Steps:

Suppose x1, x2, ..., Xm are N x 1 vectors

Step 1: $\bar{x} = \frac{1}{M}\sum_{i=1}^{M} x_i$

Step 2: Subtract the mean $\emptyset_i = x_i - \bar{x}$

Step 3: From the matrix $\mathrm{A} = [\emptyset_i \ \emptyset_i \ \dots \dots \dots \dots . \emptyset_M]$ (N x M matrix), then compute:

$$\mathrm{C} = \frac{1}{M}\sum_{n=1}^{M} \emptyset_n \emptyset_n^T = \mathrm{A}A^T$$

(Sample covariance matrix, N x N, characterizes the scatter of the data)

Step 4: Compute the eigenvalue of C: $\lambda_1 > \lambda_2 > \cdots > \lambda_N$

Step 5: Compute the eigenvector of C: $u_1, u_1, \dots, u_N$

Since C is symmetric, $u_1, u_1, \dots, u_N$ from a basis, (i.e. any vector x or actually $(x_i - \bar{x})$, can be written as a linear combination of the eigenvector):

$$x_i - \bar{x} = b_1 u_1 + b_2 u_2 + \cdots + b_n u_N$$

$$= \sum_{i=1}^{N} b_i u_i$$

Step 6: (Dimensionality reduction step) keep only the term corresponding to the K largest eigenvalues:

$$\hat{x} - \bar{x} = \sum_{i=1}^{N} b_i u_i \text{ Where K << N}$$

The representation of $\hat{x} - \bar{x}$ into the basis $u_1, u_1, \dots, u_K$ is thus $\begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix}$

$$\begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix} = \begin{bmatrix} u_1^T \\ u_2^T \\ \vdots \\ u_K^T \end{bmatrix} (x - \bar{x})$$

$$= U^T (x - \bar{x})$$

3.4.2 Non-negative Matrix Factorization

Non-negative matrix factorization (NMF), also non-negative matrix approximation is a group of algorithms in multivariate analysis and linear algebra where a matrix V is factorized into (usually) two matrices W and H as shown in Fig.3.7, with the property that all three matrices have no negative elements. This non-negativity makes the resulting matrices easier to inspect. Also, in applications such as processing of audio spectrograms non-negativity is inherent to the data being considered. Since the problem is not exactly solvable in general, it is commonly approximated numerically.

NMF finds applications in such fields as computer vision, document clustering, audio signal processing and recommender systems.

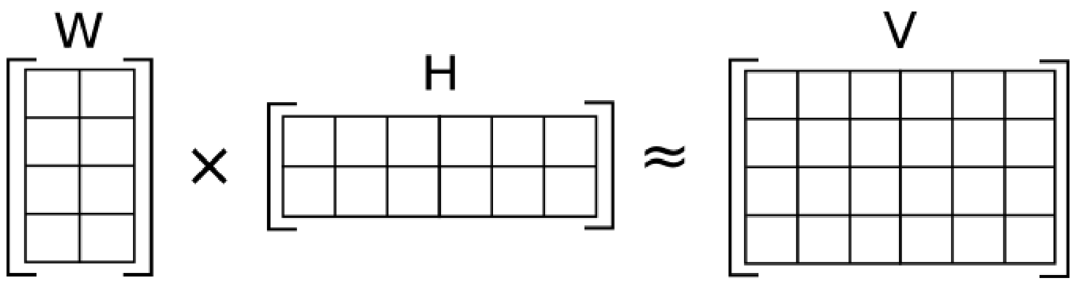


Fig.3.7 Illustration of approximate non-negative matrix factorization: the matrix V is represented by the two smaller matrices W and H, which, when multiplied, approximately reconstruct V.

An m x n non-negative data matrix X, where each column is a sample vector, can be approximated by NMF as

$$X = WH + E$$

where E is the error and W and H have dimensions m x r and r x n respectively. When E ≈ 0, the NMF equation simplifies to

$$X = WH$$

The decomposition of X into W and H can be determined by optimizing an error function between the original data matrix and the decomposition.

Update equation

$$H\ (n + 1) = H\ (n) \times \frac{W^T.X}{(W^T W.H)}$$

$$W\ (n + 1) = W\ (n) \times \frac{X.H^T}{(W.H.H^T)}$$

The full NMF model is written as

$$X_{m\times n} = W_{m\times r}\ \times\ H_{r\times n}$$

$$X_{m\times n} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}$$

$$W_{m\times r} = \begin{pmatrix} w_{11} & \cdots & w_{1r} \\ \vdots & \ddots & \vdots \\ w_{1m} & \cdots & w_{rm} \end{pmatrix}$$

And $$H_{r\times n} = \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_r \end{bmatrix}$$

Limitation of NMF

NMF is not suitable for learning parts for complex cases, which require fully hierarchical models with multiple levels of hidden variables.

NMF does not learn anything about the “syntactic” relationships between parts: NMF assumes that the hidden variables are nonnegative, but makes no assumption about their statistical dependency.

Chapter-4

Method Description

Implementation consists of following steps:-

a) Data acquisition
b) Feature transformation
c) Feature extraction
d) Classification
e) Feature selection

This chapter presents brief description of above mentioned steps.

4.1 Brief Description of Data

We have taken dataset from [18] for hand motion. Data recording which had been recorded by experiment. The following tasks were performed respectively:

1) Skin preparation is done by wiping the muscle area by alcohol to remove dead skin and made hair free.

2) Sequence of hand movement displayed on monitor orderly to guide the subjects, while performing.

3) Four muscles selected on right arm subject & data recorded. The samples of data collected for 10 subjects having 6 trials of each subject and 20,000 samples were recorded for 10 seconds each.

4) Ten different finger movements were performed one by one with five simple and five complex movement of hand. The movement list is as follows:

i. Thumb (T)
ii. Index (I)
iii. Middle (M)
iv. Ring (R)
v. Little (L)
vi. Thumb index(TI)
vii. Thumb middle(TM)
viii. Thumb ring (TR)
ix. Thumb little (TL)
x. Hand close (HC)

A resting time span of five minutes was given between each hand movement and the experiment performed without any interference.

4.2 METHODOLOGY

The sEMG data has been resampled to 1000 sample/sec, original sampling rate was 4000 sample/sec. The resample data is then rectified and divided into overlapping window of 256 samples length with a 64 samples increment (25 % overlapping) between window, by which data loss may be less as we go through overlapping. The EMG signal of the performing hand muscles is detected by electrodes connected to a sensor The signals has been pre-processed first in order to qualify the incoming raw signal for further processing. The pre-processing steps include amplification of the signal and reduction of noise.

The NMF and PCA have been used for dimension reduction as explained earlier [3.4]. Then two features have been extracted for training the classifier. These features have been also used for classification. Four algorithms namely ANN, KNN, SVM, and Discriminant analysis have been used for classification and accuracy of these methods have been compared.

4.3 Extracting the EMG signal

The brief description of data taken from [18] is as follows:- The system used is Biopac-system MP 150 which records data at a speed of 400 kHz (Aggregate). It record multiple channels with variable samples rates to maximize storage efficiency. It records EMG data in an active range of 10 to 500 Hz for surface EMG and for nerve i.e. needle electrode it can be set to 100 to 5000 Hz. For recording the EMG data the EL-500 series disposable electrodes are used, before which these steps performed.

1) Electrode site is dry and free of excessive hair.
2) Electrode is not placed over scar tissue or on an area of established erythema or lesion.
3) Skin is properly prepared. (Prepare the skin at the electrode site. Use the ELPAD to lightly abrade the skin surface. Use a brisk dry rub to prepare the application site. Avoid excessive abrasion of the skin surface).

Four muscles on right hand selected to record the data. They are:

1) Flexor carpii radialis (FCR)
2) Extensor carpii ulnaris (ECU)
3) Pronator teres (PR)
4) Bicep brachii long head (BLH)

All which are responsible for the selected hand gestures.

4.4 Preprocessing

This includes filtering, segmentation and noise removal of data.

4.5 Feature Transformation

After signal processing two, dimension reduction techniques i.e., PCA and NMF have been used to reduce the dimension of real data. NMF technique factorizes the data into two matrices W and H and gives a non-negative matrix vector, while PCA factorizes data into independent components.

4.6 Feature Extraction

For classification of hand movements distinctive features have been obtained for each signal. The features should be selected in such a way so that they are simple, easy and reliable. They are RMS, MSV, MAV, WL, entropy, skew, energy, kurtosis, mean average and log value. These feature extraction techniques are implemented with the help of MATLAB as the functions where described on the software.

Rms	7.14732547
Msv	5.10842596

Table 4.1 List of features collected

4.7 Classification

We used four different methods to classify the hand movements.

Classification evaluation is performed in terms of percentage accuracy. Implementation has been done in MATLAB software. The data input is given in XLSX file format. Data processing, classification and data is visualized in 2 dimension format. Following four classification methods have been used:-

1) Artificial neural network(ANN)
2) Discriminant analysis

3) Multi-svm
4) Kohenean Nearest Neighbor(K-NN)

4.7.1 Artificial neural network

Feedforward network combined with resilent backpropagation algorithm for neural network function is used here. MATLAB function “Trainrp” is a network training function, which has been used to updates weight and bias values according to the resilient backpropagation algorithm (Rprop).

net.trainFcn = 'trainrp'

4.7.2 Discriminant analysis

It assumes that different classes produce data on the basis of Gaussian distributions. “fitcdiscr” function is used to train (create) a classifier, the fitting function approximate the parameters of a Gaussian distribution for each class.

To predict the classes of new data, the trained classifier locates the class with the minimum misclassification cost using the function “predict”.

Each class generates data using a multivariate normal distribution. In other words, the model assumes has a Gaussian mixture distribution (gmdistribution).

For linear discriminant analysis, the model has similar covariance matrix for every class; only the means differ. “fitcdiscr” infers the mean and covariance parameters of each class.

In case of linear discriminant analysis, it computes the sample mean of each class. After that it calculates the sample covariance by first subtracting the sample mean of each class from the observations of that class, and taking the empirical covariance matrix of the result. The fit method does not use prior probabilities or costs for fitting.

4.7.3 Kohneean nearest neighbor (KNN) Classifier

A nearest-neighbour classification object, where both distance metric ("nearest") and number of neighbours can be altered. The object classifies new observations using the predict method. The object contains the data used for training, so can compute re substitution predictions. “fitcknn” creates a k-nearest neighbour classification model. Nearest neighbour fitting speed is high and while the prediction speed is medium.

4.7.4 Multi-SVM

This is used for multi-class classification in which models have a training set with a corresponding group vector and classifies a given test set using an SVM classifier according to a one verses all relation. Ten classes have been classified using multi-svm.

CHAPTER-5

Simulation Results and Discussion

5.1 Simulation

This chapter presents results of finger movements classification of 10 different subjects using the EMG signals. Efficacy of proposed algorithm is demonstrated by considering these 10 finger movement into simple and complex class. The proposed technique using non-negative matrix factorization method outperforms the existing method like principle component analysis in terms of classification process.

Input Image

We loaded the data which has xlsx format. The sEMG data which have 20,000x2 samples of 2 channels each for each trial and 6 such trials are recorded for 1 subject, which comprises of the finger movements. The overall data consist of two channels, hence two frames of each movement has been used. Fig. 5.1 shows the input data for hand movement “Thumb flexor”. These data are collected using the BIOPAC MP 150 toolkit in the laboratory.

Butterworth filter and rectification

We used 10^{th} order low pass filter high pass filter is applied on the original image. Then, to improve the quality of collected data, filtration is done. The EMG signals are then bandpass filtered between 10 and 400 Hz with a notch filter implemented to remove the 50 Hz line interference. Ten classes of individual and combined fingers movements were implemented including: the flexion of each of the individual fingers, i.e., Thumb (T), Index (I), Middle (M), Ring (R), Little (L) and the pinching of combined Thumb–Index (T–I), Thumb–Middle (T–M), Thumb–Ring (T–R), Thumb–Little (T–L), and finally the hand close (HC) as shown in the figures within the dataset. As the filtration process is implemented on to it, movement artefact (<10 Hz), power-line interference (50 Hz) and high-frequency noise (>400 Hz) are also removed and gives better visibility to the data. Fig 5.2 shows the filtered images. Then the EMG datasets are rectified.

Segmentation Process

After filtering the data, segmentation of data has been performed. This includes windowing of data. The sEMG data are sampled to 1000 samples/sec., rectified and divided into overlapping windows of 256 samples length with a 64 samples increment (25% overlapping) between windows. This segmentation scheme is used for all numerical experiments in this study. One of the examples of the rectified and sampled windows used for the NMF source separation algorithm is shown in Fig. 5.3. Thus, two frames of 20,000x2 samples are divided into segmented data.

Feature Transformation

Feature transformation is a group of methods that create new features (predictor variables). The methods are useful for dimension reduction when the transformed features have a descriptive power that is more easily ordered than the original features. In this case, less important features can be dropped from consideration.

We used NMF and PCA for this purpose and compared the results.

1. Non-negative matrix factorization - NMF strictly converts both matrices W and H to have nonnegative entries, which means that the data can be described using only positive components. Hence, the obtained decomposed matrixes express the original matrix by linear combination of only additive components. A non-negative data matrix X, where each column is a sample vector, can be approximated by NMF as WxH. Here, 100 iterations and 2 vector basis has been taken and the result obtained using the NMF algorithm is shown in Fig.5.4 below with matrix W and H of dimension 1000x2 and 2x2 respectively.
2. Principle component analysis: This method of dimension reduction is carried out in MATLAB using inbuilt function. The results obtained from the PCA analysis is shown in Fig. 5.5

Feature Extraction

In this process, the reduced data are collected as a whole and two feature values are extracted from the processed data as shown in Fig.5.6. The features calculated have significance and each feature have dimension of 26x60 which is further unified. The features namely root mean square and mean average value have been used in this work. The features are calculated for each of the dimension reduction methods, namely, PCA and NMF.

(a) Results using NMF Method

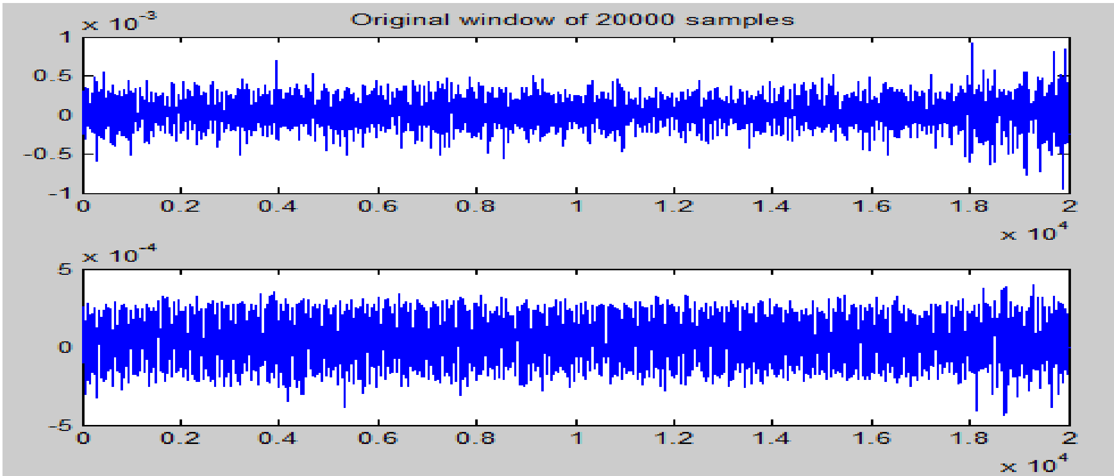


Figure 5.1: Signal

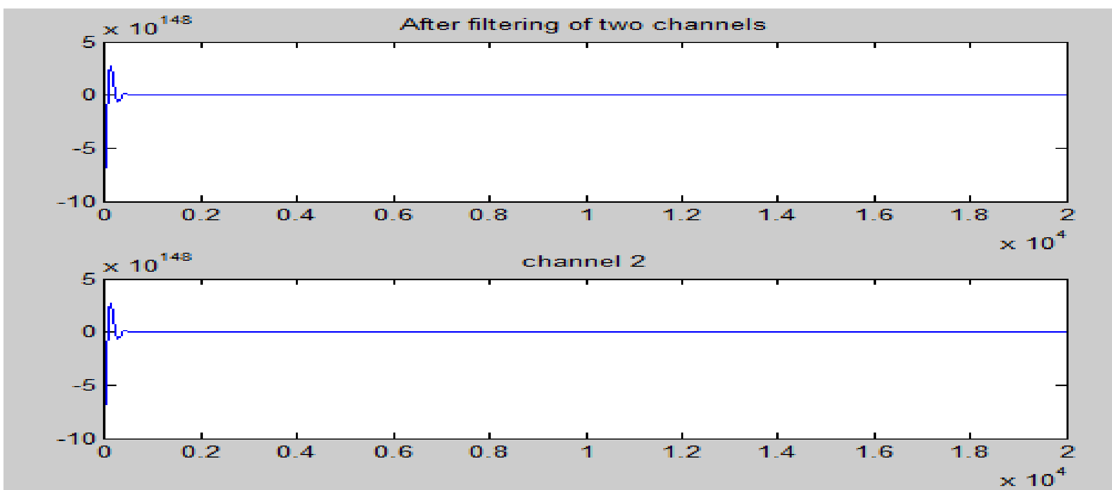


Figure 5.2: Filtered Signal

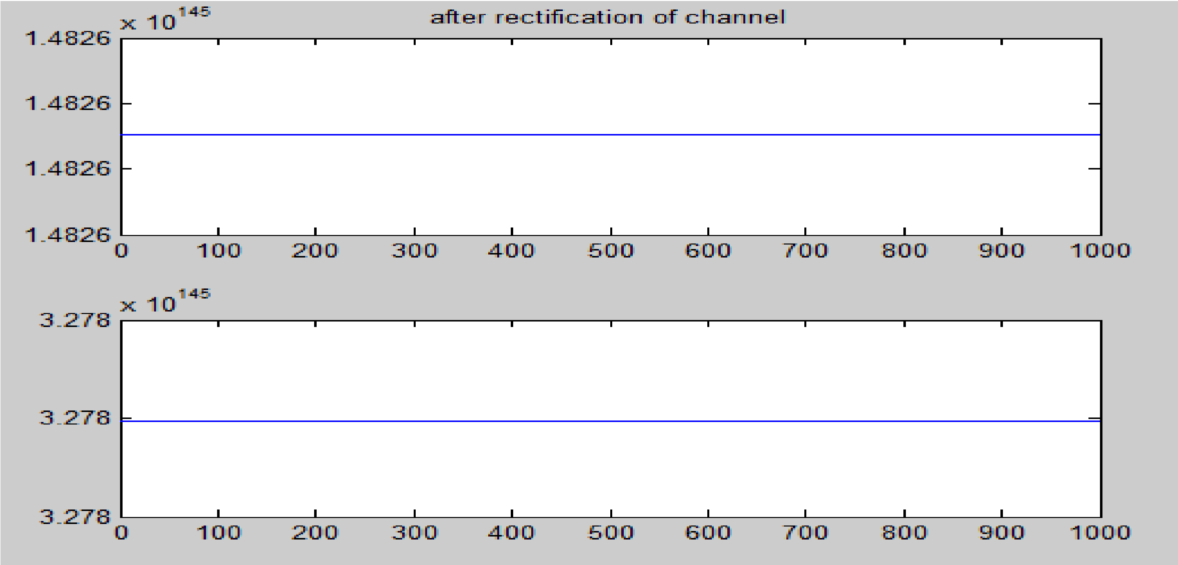


Figure 5.3: Rectified Signal

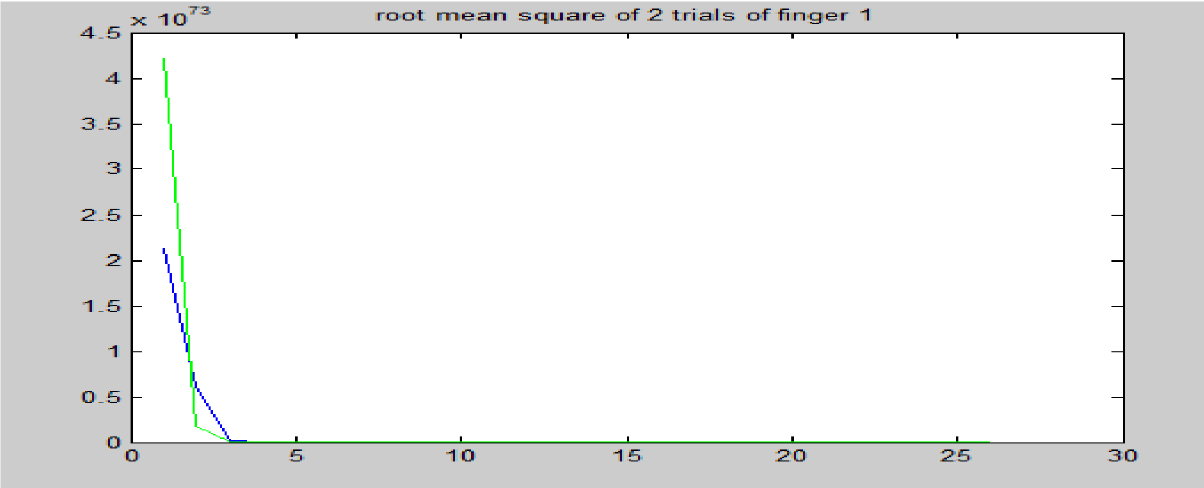


Figure 5.4: Root mean square value

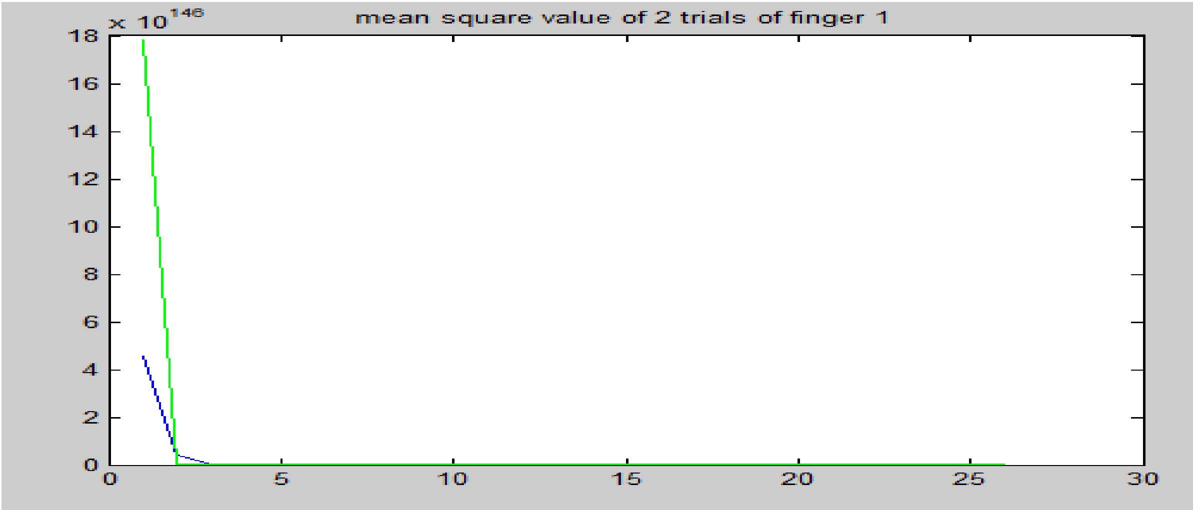
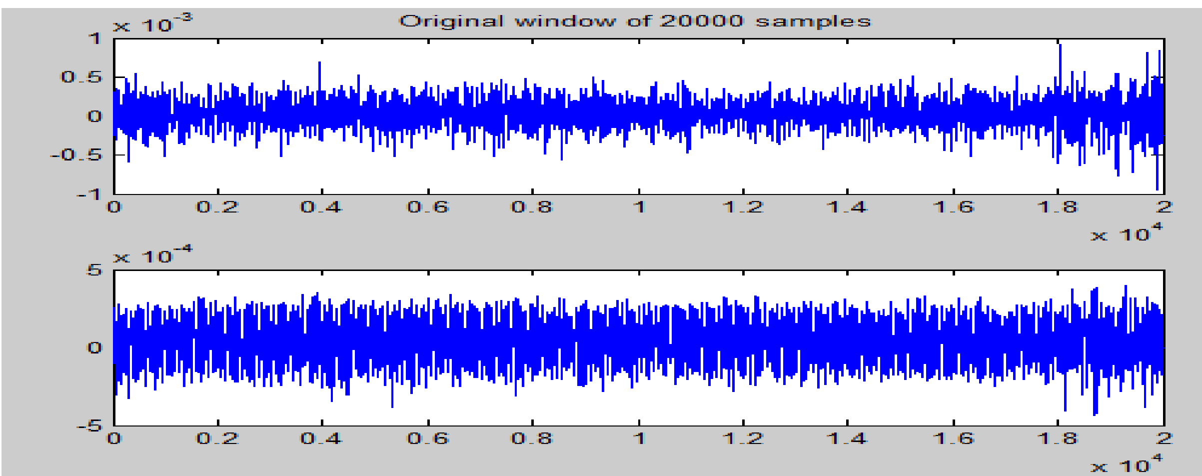
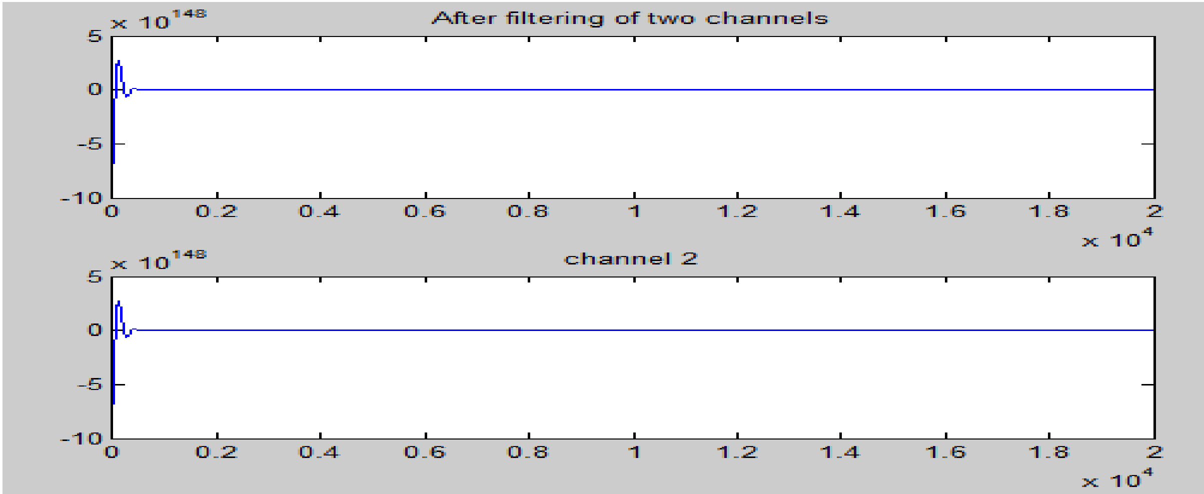


Figure 5.5 : Covariance

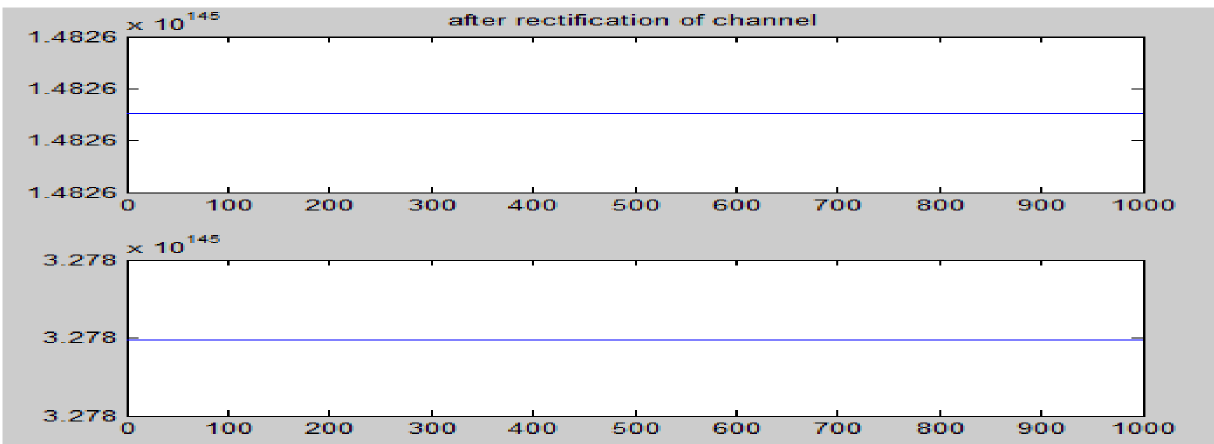
(b) Results from PCA Method



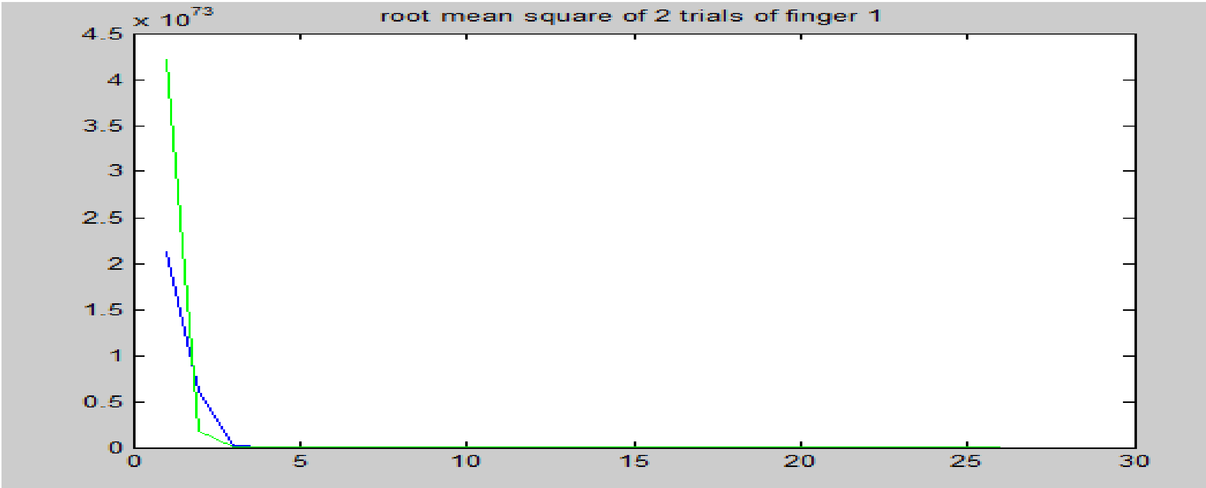
fig(5.6) Window Signal



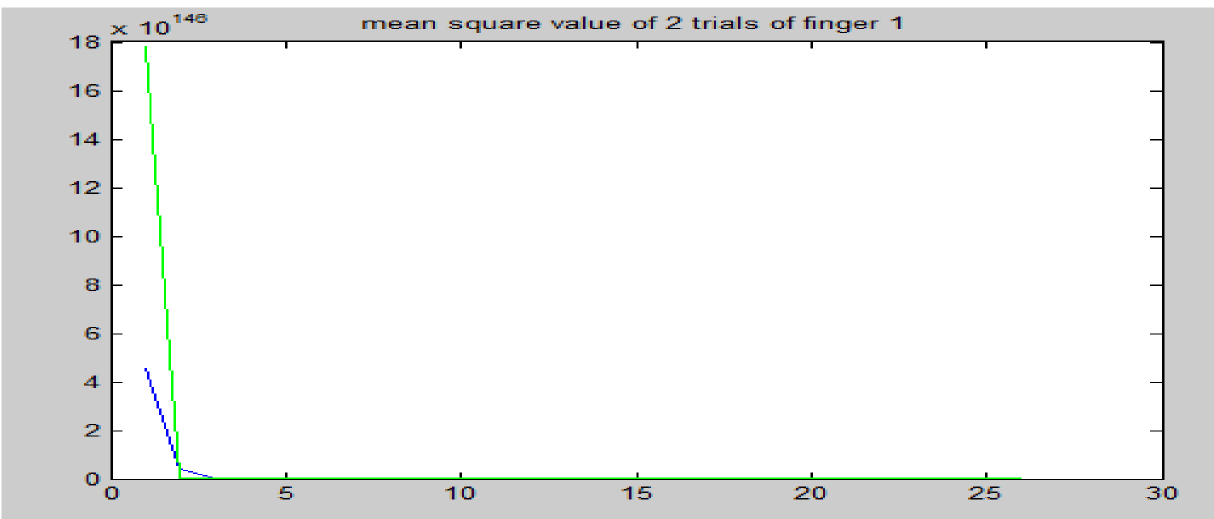
fig(5.7) Filtered Signal



fig(5.8) Rectified Signal



fig(5.9) Root mean squared signal



fig(5.10) Covariance

1.2 Classifier performance

Four different classification schemes are implemented on the result obtained from both NMF and PCA described as follows:

1. ANN CLASSIFIER: A defined feed forward neural network, initialize with resilient (trainrp) has been used. The parameters used to evaluate the optimized training performance are :- number of hidden neurons, performance, number of iterations,

time and validation. The tuning of these parameters have been done to get optimized training performance. By fixing the values of these parameters as in Table 1, the optimized training performance is obtained.

Number of hidden neurons	Values
No of hidden neuron 1 No of hidden neuron 2	10 20
Performance	0.00728
No of iterations	5000
Time	0:00:66

Table 5.1: Various Parameters setting for ANN to get optimized training performance by NMF method

The performance of the evaluation of NMF data is given in terms of ROC plot for neural network classifier. The plot of ROC curve with neural network classifier is given below:

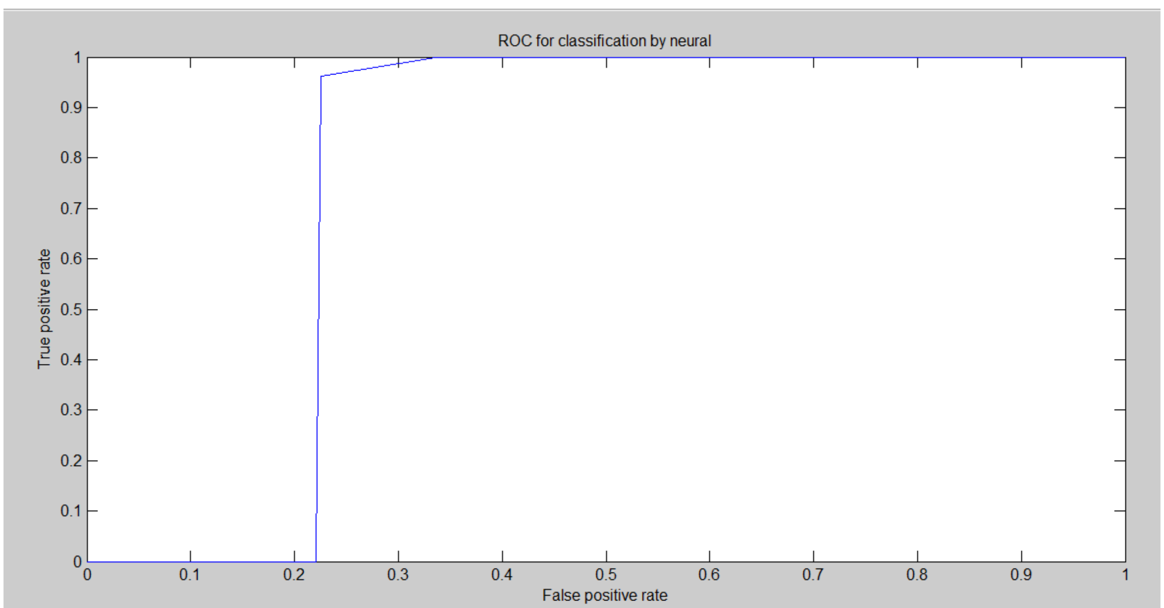


Figure 5.11: ROC plot for ANN classifier for testing data evaluation by non-negative matrix factorization method.

2. Discriminant Analysis:

The optimized training performance in the case of the discriminant analysis classifier has been obtained using the MATLAB function “fitdiscr”. Distance “pseudolinear” is used to train the parameters and “predict” function is used to test the data. The results obtained from both the dimension reduction method are shown in a tabular form.

3. K-Nearest Neighbour Classifier:

To classify the data using KNN classifier “fitcknn” function has been used to set the targets and “NumNeighbors” distance method has been implemented. The tuning of parameters have been done to obtain the accurate results.

4.Multi- SVM Classifier:

Multi-SVM uses a multi class formulation and optimize the data using the algorithm described in chapter 3. Hence, it classify the data using both the NMF and PCA method while tuning some parameters of the system.

The result obtained comprises of the 4 classification methods using both NMF and PCA method (for feature reduction) and 10 finger movements are classified as given in table:

SUBJECT	Methods	
	PCA	NMF
T	78	99
I	94	98
M	07	99
R	98	100
L	95	96
TI	96	97
TM	96	95
TR	95	99
TL	98	99
HC	98	99

Results obtained from the neural network classifier in terms of % for 10 finger movements.
Also the results obtained from four different classifiers namely ANN, KNN, Discriminant analysis and multi-svm have been shown in terms of bar-graph.

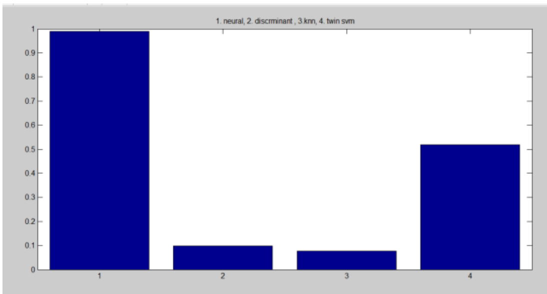


Fig. 5.12: Result obtained using NMF

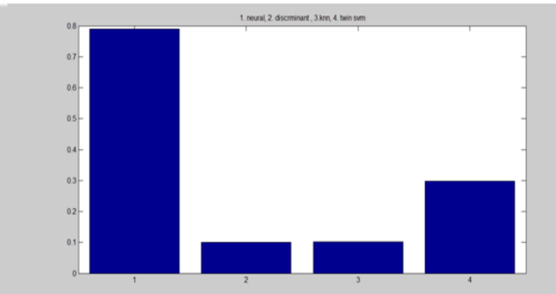


Fig. 5.13: Result obtained using PCA

Comparisons of the Classifiers Performance

After calculating the Classification rate, using both PCA and NMF method for the various classifiers, a comparison has been made based on accuracy rates for different hand movements. The Table 5.2 gives the comparison results with respect to four classifiers and non-negative and factorization method. From these comparisons, the outcome as the NMF gives better performance with ANN having 97.5% accuracy, which is much better than PCA method and other classifiers.

Classifier	% Accuracy by PCA	% Accuracy by NMF
Artificial Neural Network	84.5	95
Discriminant Analysis	10	17
K-Nearest Neighbor	11	19
Multi-SVM	29	32

Table 5.2 Comparison of NMF and PCA in terms of percentage accuracy

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

Conclusion

We have described a system that demonstrates the sEMG classification by using MATLAB software and classifying the data with four different techniques. A comparison is done based on two feature transformation techniques namely NMF and PCA. Discriminant analysis gives 17% classification rate for the NMF method while 10% for the PCA. Nearest neighbor classifier gives 11% classification rate and 19% for NMF and PCA respectively. A multi-SVM classification technique for NMF gives 32% and for PCA gives 29% classification rate. Artificial neural network which work on neural learning technique gives 95% classification rate using NMF method and 84.5% using PCA.

Also, implementing the above work on MATLAB software save a lot of time and is reliable. More recently, researchers in areas such as bioinformatics are becoming increasingly aware of the usefulness of machine learning techniques alongside the more traditional statistical techniques. The efficiency and scalability of the presented technique also makes it well suited to the domain of medical image analysis for feature extraction and clustering of similar feature based rules.

Future scope:-

Large number of features can be extracted form the signal for better training and classification of signals.

References

1. Alkan, A.; Günay, M. Identification of EMG signals using discriminant analysis and SVM classifier. *Expert Syst. Appl.* **2012**, *39*, 44–47.

2. Reaz, M.B.I.; Hussain, M.S.; Mohd-Yasin, F. Techniques of EMG signal analysis: Detection, processing, classification and Applications. *Biol. Proced. Online* **2006**, *8*, 11–35.

3. Shyu Liang-Yu el al. Electrode placement in surface electromyography (sEMG) Minimal Crosstalk Area (MCA). *Open Rehabil. J.* **2002**, *3*, 110–126.

4. Yonghong Huang, Kevin B. Englehart, Bernard Hudgins A Gaussian Mixture Model Based Classification Scheme for Myoelectric Control of Powered Upper Limb Prostheses. In Proceedings of the IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 52, NO. 11, NOVEMBER 2005.

5. Wang, S.; Gao, Y.; Zhao, J.; Yang, T.; Zhu, Y. Prediction of sEMG-Based Tremor Joint Angle Using the RBF Neural Network. In Proceedings of 2012 IEEE International Conference on Mechatronics and Automation, Chengdu, China, 5–8 August 2012; pp. 2103–2108.

6. Rami N. Khushaba*, Adel Al-Jumaily, Ahmed Al-Ani Evolutionary fuzzy discriminant analysis feature projection technique in myoelectric control. **2009**, 699–707.

7. Keehoon Kim and J. Edward Colgate, Haptic Feedback Enhances Grip Force Control of sEMG-Controlled Prosthetic Hands in Targeted Reinnervation Amputees, NOVEMBER2012 ; VOL.20,NO.6.

8. Chu, J.U.; Moon, I.; Lee, Y.J.; Kim, S.K.; Mun, M.S. A supervised feature-projection-based real-time EMG pattern recognition for multifunction myoelectric hand control. *IEEE/ASME Trans. Mechatron.* **2007**, *12*, 282–290.

9. Hussain, M.S.; Reaz, M.B.I.; Yasin, F.M.; Ibrahimy, M.I. Electromyography signal analysis using wavelet transform and higher order statistics to determine muscle contraction. *Expert Syst.* **2009**, *26*, 35–48.

10. Ganesh R. Naik, Member, IEEE, and Hung T. Nguyen, Non Negative Matrix Factorisation for the Identification of EMG finger movements: Evaluation using matrix analysis, IEEE Journal of Biomedical and Health Informatics, March 2015.

11. Vincent Carriou et al. have proposed a fast generation model of high density surface EMG signals in a cylindrical conductor volume **2016**, *9*, 6312–6329.

12. D. Johansen, the feasibility of using an inductive tongue control system (ITCS) for controlling robotic/prosthetic hands and arms and a dual modal control scheme for multi-grasp robotic hands combining standard EMG with the ITCS. *IEEE Eng. Med. Biol. Mag.* **2016**, *24*, 63–72.

13. Adenike A. Adewuy, J.N.F.; Luk, K.D.K. Effect of electrocardiographic contamination on surface electromyography assessment of back muscles. *J. Electromyogr. Kinesiol.* **2016**, *19*, 145–156.

14. https://en.wikipedia.org/wiki/Artificial_neural_network

15. http://www.rami-khushaba.com/electromyogram-emg-repository.html