EEG BASED EMOTION RECOGNITION USING HIGHER ORDER CROSSINGS

A Dissertation submitted in fulfillment of the requirements for the Degree
of

MASTER OF ENGINEERING
in
Electronic Instrumentation & Control Engineering

Submitted by

Sonakshi Bhardwaj
801451025

Under the Guidance of

Mr. Mooninder Singh
Assistant Professor, EIED

2016

Electrical and Instrumentation Engineering Department
Thapar University, Patiala
(Declared as Deemed-to-be-University u/s 3 of the UGC Act., 1956)
Post Bag No. 32, Patiala – 147004
Punjab (India)

DECLARATION

I hereby certify that the work which is presented in dissertation entitled, "**EEG Based Emotion Recognition Using Higher Order Crossings**" in partial fulfilment of the requirements for the award of the degree of Master of Engineering in Electronics (Instrumentation & Control), submitted to Electrical & Instrumentation Engineering Department of Thapar University, Patiala is as authentic record of my own work carried under the supervision of **Mr. Mooninder Singh**, Assistant Professor, Electrical and Instrumentation Engineering Department, Thapar University, Patiala, Punjab. It refers others researcher's work which are duly listed in the reference section. The matter contained in this dissertation has not been submitted, neither in part nor in full to any other degree to any other university or institute except as reported in text and references.

Place: Patiala

Date: 18-07-2016

Sonakshi Bhardwaj

Roll No. 801451025

It is certified that the above statement made by the student is correct to the best of my knowledge and belief.

(Mr. Mooninder Singh)
Assistant Professor
Electrical & Instrumentation Engineering Department
Thapar University, Patiala

Countersigned by:

Dr. Ravinder Aggarwal
Head
Electrical & Instrumentation Engineering Department
Thapar University, Patiala

Dr. S.S. Bhatia
Dean of Academic Affairs
Thapar University, Patiala

13/8/2016

ACKNOWLEDGEMENT

First of all, I would like to express my gratitude to **Mr. Mooninder Singh, Assistant Professor**, Electrical and Instrumentation Engineering Department (EIED), Thapar University, Patiala for his patient guidance and support. I am truly very fortunate to have the opportunity to work with him. I found his guidance to be extremely valuable. I am also grateful to **Dr. Mandeep Singh, Associate Professor**, Electrical and Instrumentation Engineering Department (EIED), Thapar University for his valuable guidance.

I am extremely thankful to our **Head of the Department, Dr. Ravinder Agarwal** as well as **PG Coordinator, Mr. Nirbhowjap Singh, Assistant Professor**, Electrical and Instrumentation Engineering Department. I would like to thank entire faculty and staff of Electrical and Instrumentation Engineering Department and my friends who devoted their valuable time and helped me in all possible ways towards successful completion of this work. I thank all those who have contributed directly or indirectly to this work.

Lastly, I would like to thank my parents and brother for their years of unyielding love and encourage. They have always wanted the best for me and I admire their determination and sacrifice.

Date — Sonakshi Bhardwaj

Place: Patiala — M.E.(EICE) 2nd year

801451025

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ALS- Amyotrophic Lateral Sclerosis

ANN-Artificial Neural Network

CNS- Central Nervous System

EEG- Electroencephalogram

EMG - Electromyogram

ERP- Event Related Potential

fNIRS- Functional Near Infrared Spectroscopy

FMRI- Functional Magnetic Resonance Imaging

GSR -Galvanic Skin Response

GAPED- Geneva Affective Picture Database

BCI -Brain Computer Interface

HOC- Higher Order Crossings

HVLA- High Valence Low Arousal

HVHA- High Valence High Arousal

LVHA- Low Valence High Arousal

LVLA- Low Valence Low Arousal

IAPS- International Affective Picture System

KNN- K-Nearest Neighbour

LDA - Linear Discriminate Analysis

MLNN- Multi Layer Neural Network

MD- Mahalanobis Distance

PNS -Peripheral Nervous System

PSD- Power Spectral Density

PET- Positron Emission Tomography

SAM- Self - Assessment Manikin

SVM- Support Vector Machine

SMO- Sequential Minimal Optimization

STFT- Short Time Fourier Transform

GELM- Graph Regularized Extreme Learning Machine

WEKA- The Waikato Environment for Knowledge Analysis

ABSTRACT

Human emotions govern our quality of relations within the society. It can be expressed as a state of mind which predicts the response of a person whether positive or negative to a particular situation. It is a versatile phenomenon which controls the reactions and behaviour of the person depending upon his mental state whether he is happy, angry, frustrated, sad, excited and scared. Emotions can be predicted from gestures, sound processing and facial expression can be faked but emotion recognition using EEG signals is very powerful method to know the internal state of mind accurately. In this dissertation, the aim of the study is to design an interactive and a smart two class system for emotion recognition based on Electroencephalogram (EEG) signals. In this study EEG signal is acquired on frontal electrodes such as F1, F2, F3, F4 and FZ, central electrode Cz and parietal electrode Pz from eight subjects for classification of emotions into two classes namely HVLA (High Valence Low Arousal) and LVHA (Low Valence High Arousal). The images provided by International Affective Picture System (IAPS) have been used for evoking emotions. The data has been acquired in two ways, one by placing an EEG cap on the head of a subject as per 10-20 International system, using BIOPAC data acquisition unit. The obtained EEG signal has been filtered in offline mode (ACQ 4.2 software) by using low pass IIR filter, high pass IIR filter and a notch filter. The low pass IIR filter is followed by high pass IIR filter. IIR filters have been used to bring the EEG signal in the frequency range of 0.5 to 40Hz. The notch filter has been used to remove the 50Hz power noise interference and second by acquiring EEG signal from the data available on the enterface 06 website. The analysis has been performed using frontal electrodes F1, F2, F3, F4, and Fz, central electrode Cz and parietal electrode Pz. After EEG data acquisition, the acquired EEG signal is signal conditioned using the EDF Browser. Firstly, a Butterworth Band pass filter of 0.5 Hz to 40 Hz has been applied on the EEG Signals to bring the signal in the desired range, followed by a Resonator Notch filter with notch frequency of 50 Hz, to remove the power noise interference in the signal. Then averaging of EEG signal for each of the seven channels F1, F2, F3, F4, Fz, Cz and Pz is performed on which an IIR Butterworth Bandpass filter is applied to keep only alpha band (8-12 Hz) frequencies and beta band (13–30 Hz) frequencies. Then features called Higher Order Crossings i.e. zero crossing counts are extracted for Emotion Classification. The classification has been performed using two classifiers – Support Vector Machine (SVM) and k-Nearest Neighbour (k-NN) with 10 fold cross validation to classify emotions into two classes.

CHAPTER 1

EMOTION AND HUMAN BRAIN

1.1 Introduction

What is an emotion? *It is a mental or physiological condition which is subjective and private involving a lot of feelings, thoughts, behaviours and actions*. Emotions play a very important role in our daily lives. Emotion helps in making interaction with the people smooth. A person's mood not only affects his way of interacting with people, but also his actions. For instance, emotion of anger or sadness can prove fatal to the driver as well as to others on the way. Emotions play a very important role in our day to day activities. We tend to decide on the basis of our moods. For example, if a man says "OK" then he might say it in a happy mood or else with discontent [1]. Thus it is essential to study and recognize emotions. Emotions are easily comprehended by speech, behaviour and facial expressions [2]. But these can be falsely expressed by humans. Also, these ways cannot be efficiently exploited by those suffering from paralysis, stroke, ALS [3] or disorders associated with brain. Therefore, Emotion Recognition is essential for people in locked-in conditions. Thus, it is significant to study physiological variables that vary with emotions. This dissertation focuses on emotion recognition based on electro-encephalogram (EEG) signals. EEG is a means of recording electrical signals of brain [4]. EEG is a simple, fast, non-invasive and inexpensive method which is immensely used in biomedical research and medical diagnosis. Thus, EEG is a preferable technique for classification of emotions [5].

1.2 Problem statement

Brain Computer Interfaces (BCIs) help people in interacting with the surroundings and controlling devices by using thoughts i.e. brain activities [6]. BCIs are being utilized in classifying emotions and are considered as a helpful method as emotions are produced in the brain. As discussed by Wang et al. [7], BCIs systems have been used in rehabilitation, e.g., speller systems, neuroscience, e.g., monitoring attention systems and treatment of attention-deficit hyperactivity disorder. There are several challenges in using BCIs systems for recognizing emotions, such as the choice of the method and the channels of acquisition of brain signals that provide best information related to the emotional state of an individual and the classifiers to attain a good accuracy in the recognition of emotions.

1.3 Basic Emotions

Many researchers have given different models related to emotions. The first and foremost model was given by Darwin and was further developed by other two scientists named Plutchik and Ekman. According to Plutchik, there are basically eight emotions such as sadness, anger, joy, acceptance, disgust, surprise, fear, and curiosity [8] while Ekman suggested that all emotions comprises of six basic feelings that are happiness, anger, fear, sadness, disgust and surprise [9]. Figure 1.1 shows the basic emotions felt in our daily lives.

Figure 1.1: Basic Emotions

1.4 Quantification of Emotionss

Russell, J.A. (1980) developed a circumplex model of affect describing the emotions in a two dimensional space. This model represents the interconnection of emotions like anger, fear, happiness, joy, depression and displeasure. The emotional states were considered as pleased along the x-axis and the level of activation along the y-axis. Words describing these emotions were placed in such a way that the like meaning words were closer to each other whereas the opposites lied diagonally [10]. This model was further modified by Lang et al. who represented the two dimensions as valence and arousal [11]. Figure1.2 shows the circumplex model of affect.

Figure 1.2: Circumplex Model of Affect

1.4.1 Emotions in 2-Dimensional Plane

An Emotional Model consists of two dimensions- Valence on X-axis and Arousal on Y-axis. Valence and arousal are defined by Self-Assessment Manikin Method. SAM ratings range between 1 to 9.Valence can be represented as positive or negative state of emotions. The highest value of valence indicates a person is happy and lowest value of valence indicates a person is sad. Similarly, Arousal is defined on SAM scale from 1 to 9.The highest value of arousal indicates a person is excited and lowest value of arousal indicates a person is unexcited or calm.

1.4.2 Classes of Emotions

Emotions represented along Valence Axis and Arousal axis results into four quadrants. Valence along X-axis has been divided into two main classes called Positive Valence which means high and Negative Valence which means low and keeping the arousal state as constant. Likewise, arousal along Y- axis has been divided into two major classes namely Positive Arousal meaning high and Negative Arousal meaning low keeping the valence state as constant. It results into four major classes of emotions such as High Valence High Arousal (HVHA), Low Valence High Arousal (LVHA), High Valence Low Arousal (HVLA) and Low Valence Low Arousal (LVLA). Figure 1.3 shows the four classes of emotions.

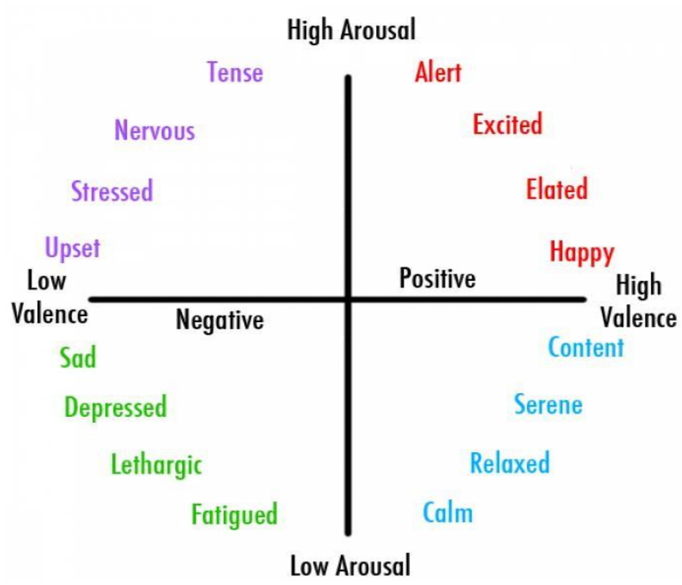

Figure 1.3: Dimension of Emotions

1.5 Brain Computer Interface

Brain Computer Interface (BCI) refers to the interaction between the computers and humans. Computers are usually unable in understanding the requirements of human beings to respond instantly, so it is not possible to correctly identify all the human emotions to take the required actions. Human computer interface implementations assist us in entertainment, electronics, military and civil aviation and in medical profession to understand the human emotions [7]. A person suffering from serious illness may be unable to interact with the environment. So, this requires the study of brain and physiological signals and then using them in human computer implementation for understanding the human emotions. BCI system comprises of different components such as signal acquisition, signal conditioning, feature extraction, classification and feedback presentation system. Figure 1.4 illustrates an affective brain computer interface system.

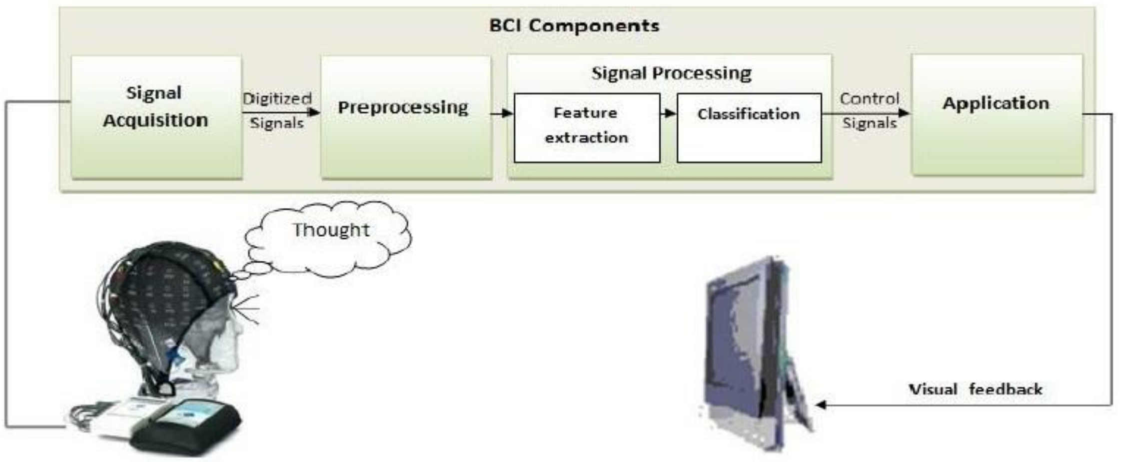

Figure 1.4: Brain Computer Interface

Human thoughts activate the electrical signals generated in brain which are further recorded by the signal acquisition system and these signals are filtered or pre-processed. The pre-processed signals are used in extracting the features to classify the emotions. During this processing, some feedback may be given to the users in order to take a corrective action [12]. Physiological signals acquired for emotion recognition are Blood Pressure, Respiration, Galvanic Skin Response (GSR), and Heart Rate and EEG signals etc. Generally, Central Nervous System (CNS) and the Peripheral Nervous System (PNS) result into the origin of physiological signals. Among all these physiological signals, EEG has gained more interest because an emotion is a psychological process related with brain activity [13] [14] [15].

1.6 Human Brain

Brain is an organ which serves as the centre of the nervous system. It is covered by skull located in the head of humans. It comprises of blood vessels, glial cells and neurons which are connected by trillion of more neurons. An average adult human brain weighs about 1.3–1.4 kg having a mushroom shaped structure. It acts as the controlling centre for all our actions such as sleeping, internal temperature, hunger and even breathing and almost all necessary activities required to survive in surroundings. It is divided into three parts: cerebrum, cerebellum and brainstem. Cerebrum is the largest part of the brain, the brainstem lies underneath the cerebrum, and at the back lies the cerebellum. Cerebrum controls the important functions such as thoughts, vision, touch, emotions, sensing temperature, and learning. The central part of brain is brainstem mainly responsible for regulation of respiration, hunger, and cardiac functions of human body. It consists of medulla oblongata, pons and midbrain. Cerebellum is the smallest part of the brain responsible for receiving information from the spinal cord, sensory systems, and other parts of the brain and helps in regulating motor movements [16]. Cerebral cortex forms the outermost layer of the cerebrum, consisting of four lobes:

- Frontal lobe
- Parietal lobe
- Temporal lobe
- Occipital lobe

1.6.1 Brain Lobes

Frontal Lobe- It is located in front of the parietal lobe and the temporal lobe of brain. It is one of the largest portions of brain and deals with functions such as reasoning, motor skills, high level cognition, and expressing languages. The space between tissues is called central sulcus separating frontal lobe from parietal lobe. Frontal lobe receives information from other lobes of the brain and helps in carrying out movement of body parts properly. Any damage to frontal lobe can cause mood swings.

Parietal Lobe- It is located behind the frontal lobe and the central sulcus and above the occipital lobe of brain. It is central part of the brain, separating from occipital lobe by parietal-occipital sulcus. It carries out functions associated with processing sensory information such as pressure, touch, pain from different parts of body within seconds. If parietal lobe gets damaged then one won't be able to feel the sense of touch.

Occipital Lobe- It is located at the back side of the cortex, the smallest among all paired lobes, which interprets visual stimuli and helps to understand properly what our eyes are sending to other lobes. If occipital lobe is damaged then visual problems can occur such as problem in identifying colors and recognizing objects.

Temporal Lobe- It is located inferior to parietal and frontal lobe and anterior to occipital lobe of brain. It helps in processing auditory information such as speech and sound received from the ears. If it gets damaged then visual problems, problems with memory and language skills can occur and person will not be able to listen properly.

All the lobes of brain are shown in Figure 1.5.

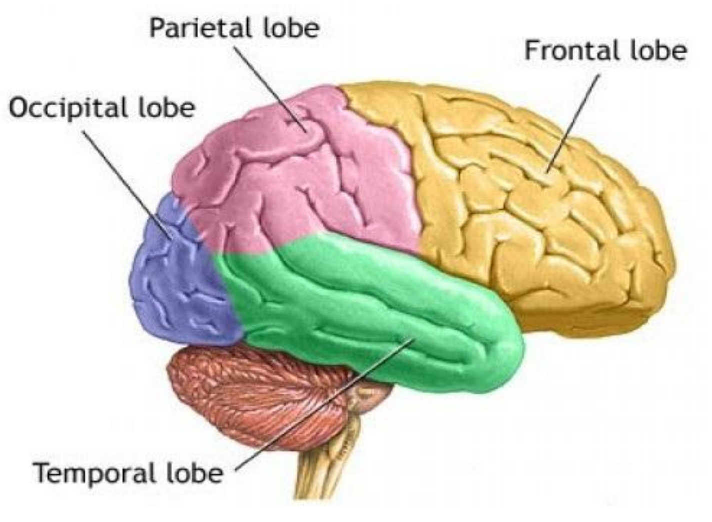

Figure 1.5: Human Brain

1.6.2 Brain Waves

Brain is an electrochemical organ which generates electrical activity in the form of brain waves while performing functions such as sleeping, thinking, etc. These waves are detected by placing sensors on the scalp. Different Brain waves are generated with different day to day activities [17], measured in Hz (cycles per second) and are of five types such as

- Delta wave
- Theta wave
- Alpha wave
- Beta wave
- Gamma wave

Delta Wave- The delta wave belongs to a frequency band up to 4Hz. Delta activity is mainly observed in deep sleep.

Theta Wave- The theta wave belongs to a frequency band of 4Hz to 8Hz. This activity can be observed when a person is feeling drowsy or in meditation state.

Alpha Wave- The alpha wave is called the basic rhythm wave and belongs to a frequency band of 8Hz to 13Hz. It is observed when people are awake, and is known to be more evident while the eyes are opened.

Beta Wave- The beta wave belongs to frequency band of 13Hz to 30Hz. This band is more evident when the person is alert or in working mode.

Gamma Wave- The gamma wave belongs to frequency band of 30 Hz to 100 Hz. This is the fastest among all the brain waves and is evident during active thinking. Different brain waves are illustrated in Figure 1.6.

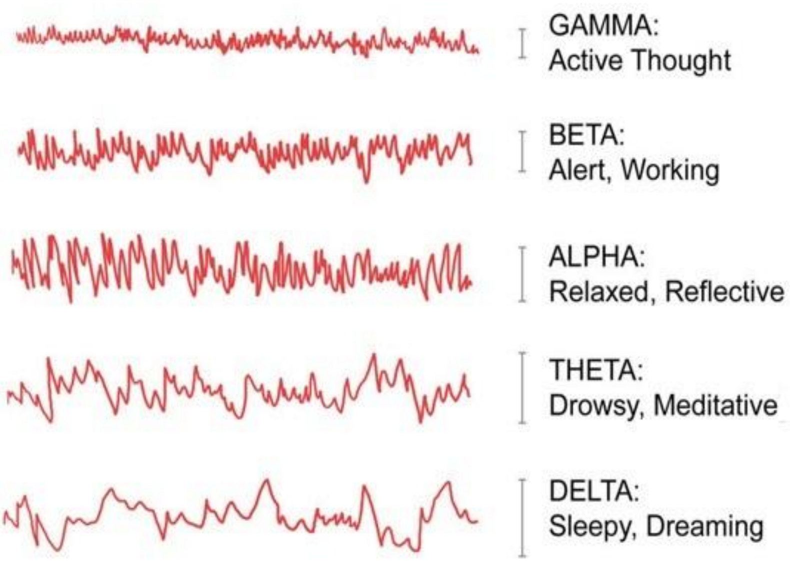

Figure 1.6: Brain Waves

1.7 EEG

EEG is a means of recording electrical signals generated in brain [4]. This electrical activity is generated due to firing of millions of neuron inside the brain and then the final electrical signal is recorded by EEG cap when the electrodes are placed on the person's scalp. Conductive gel is filled in the electrodes to make proper contact between the scalp and electrodes. One of the major applications of EEG is in identification of emotions and diagnosing epilepsy. Emotions cannot be directly identified from the EEG signal, as it requires filtering and feature extraction from the signal. Various researches have been performed for searching a proper relationship between emotions and EEG signals [18]. Using both EEG signals and peripheral signals such as Blood Pressure, Galvanic Skin Response (GSR), Respiration, and Heart Rate, classification of emotions was performed [18] [19]. But many researches gave preference only to EEG signals for emotion recognition. As emotions can be predicted from other methods also such as Positron Emission Tomography (PET), Functional Magnetic Resonance Imaging (FMRI) but these methods are very slow and are dependent on the changes in blood composition of humans [20]. So the preferable method is using EEG as it has simple and portable hardware, helps in direct measurement of electrical activity. One second of an EEG signal is depicted in Figure 1.7.

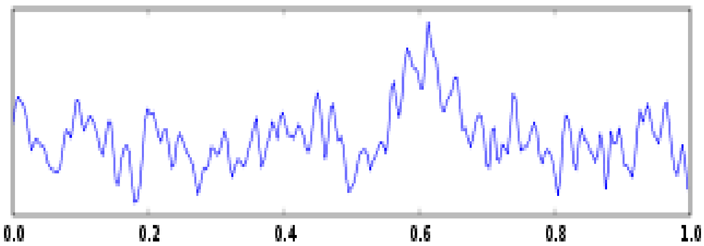

Figure 1.7: One second of an EEG Signal

1.8 Electrodes

Electrodes play an important role in EEG data acquisition. All electrodes are placed on the person's scalp to acquire the EEG signal. These electrodes make proper contact with the scalp with the help of conductive gel. The placing of these electrodes is according to international 10-20 system i.e. the actual distances between the adjacent electrodes are either 10% or 20% of the total front to back or right to left distance of the skull. These electrodes on EEG cap are referred with alphabets. The alphabets refer to different lobes of the brain such as Frontal lobe is labelled as F, Central lobe as C, Parietal lobe as P, Temporal lobe as T and Occipital lobe as O. Electrodes are marked with even number on right portion and odd number on left portion of brain. These electrodes are made up of tin, gold, silver or silver chloride. Other methods for placement of electrodes are 10-10 and 10-5 systems. But usually 10-20 system is preferred for acquiring the EEG data [21].

Figure 1.8 depicts International10-20 system.

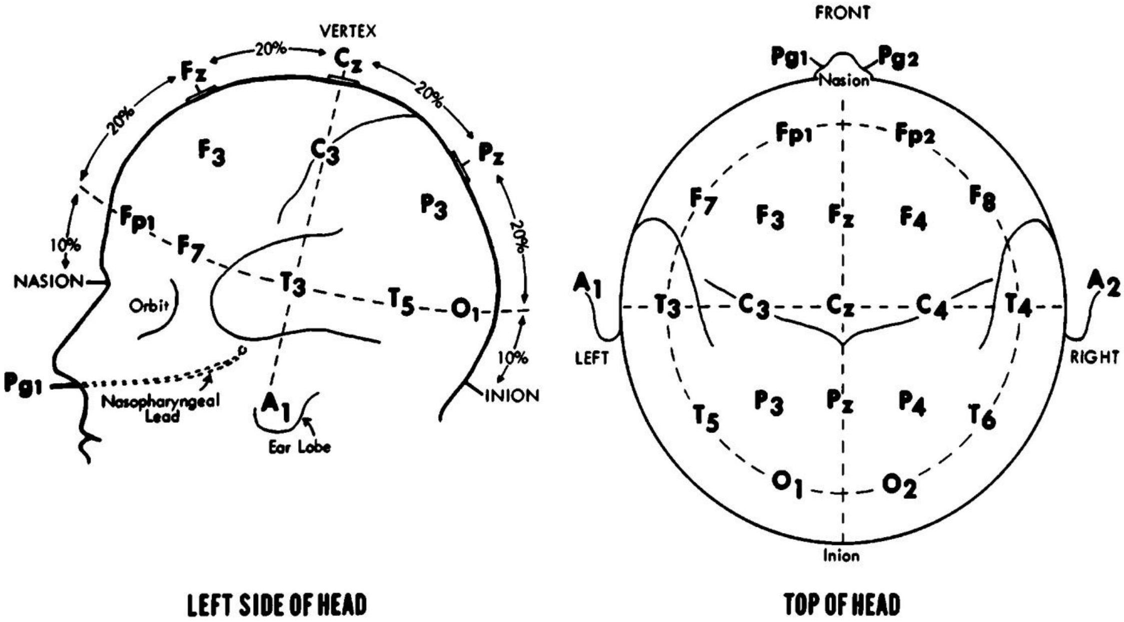

Figure 1.8:10-20 International system

CHAPTER 2

LITERATURE REVIEW

Many researchers have followed various techniques for emotion recognition and classification. Some of the researches done by various authors are discussed below:

Picard, R.W et al. (2001) classified eight classes of emotions such as love, hatred, sadness, romance, nature, joy including neutral. These emotions were evoked as per the guidelines mentioned by Clynes [22]. To recognize these emotions, data was collected from single subject with the help of four transducers such as triode EMG, skin conductance transducer, photo-plethysmyograph & Hall Effect respiration transducer. Features such as mean value and standard deviation were used for classifying emotions, using Maximum a Posteriori (MAP) classifier employing Fisher analysis algorithm achieving about 80% to 90% accuracy.

Babiloni, F et al. (2001) gathered EEG data from 8 subjects using four electrodes such as C3, C4, P3 and P4 placing them according to international 10-20 system. Features such as covariance and diagonal matrix of EEG data were extracted using quadratic classifier which employed Mahalanobis distance (MD) algorithm for classifying emotions, achieving an average accuracy of 98% [23].

Kim, K.H et al. (2004) developed a physiological database using ECG and skin temperature changes as parameters from 50 subjects. Emotions were classified into four states such as surprise, sadness, anger and stress using Support Vector Machine classifier obtaining 78% 61.8% and 78% accuracy in case of four and three distinct emotions respectively.

Takahashi, K et al. (2004) employed physiological database for classifying emotions into five states such as joy, angry, sad, happy and relax from 12 participants using Support Vector Machine classifier, achieving an accuracy of 41.7% [24].

Chanel, G et al. (2007) classified emotions into three states such as negative exciting, positive exciting and calm-neutral using the fusion of EEG and other physiological variables such as GSR, Respiration, Blood Pressure and Heart Rate. The EEG signal was collected using 64 electrodes placed according to 10-20 system from three subjects. The features extracted were mean value and STFT of EEG data for classifying emotions using LDA and SVM classifiers. The researchers concluded that using EEG signals are better than other physiological signals in classifying emotions.

Khalili, Z et al (2008) collected EEG Data from enterface06 database, using images from IAPS dataset. Classification of emotions was done into 3 classes namely Positively exciting, Negatively exciting and Calm as well as 2 classes namely Positively exciting and Negatively exciting using k-NN and Linear Discriminant Analysis (LDA), giving best accuracy of 40% for LDA, 51% for k-NN in 3 classes and 50% for LDA, 65% for k-NN in 2 classes and fusion of both EEG and peripheral signals was also studied [25].

Horlings, R et al (2008) collected EEG signals from 10 subjects and also acquired EEG Data from enterface06 database [26] ,using images from IAPS dataset. Classification of emotions was done into five classes along valence and arousal axis. The features extracted were EEG frequency spectrum power, cross-correlation among EEG spectral band powers, peak frequency in alpha band and Hjorth parameters. Classification of emotions was performed using 3 fold cross validation with artificial neural network and naive Bayes classifier. Recognition rate for neural networks was lesser when compared to naive Bayes giving an accuracy of 32% for valence and 37% for arousal dimension [27].

Frantzidis, C. A et al (2008) acquired the EEG data from CNS and SCR from 13 male and female subjects by evoking emotions using IAPS images, using three electrodes namely Fz, Cz and Pz. These IAPS images were divided into four classes such as HVHA, HVLA, LVHA and LVLA. The features extracted were ERP, latency, rise time, amplitude and the skin conductance response duration for classifying emotions using Artificial Neural Network classifier, giving an accuracy of 80% for joy, 80% for happiness, 100% for fear and 70% for hatred [28].

Murugappan, M et al (2009) gathered EEG data from 20 subjects and classified emotions into five states namely happiness, disgust, surprise, fear and neutral using Audio-visual stimuli for evoking emotions. The EEG signal was divided into various spectral bands such as delta, theta, alpha, beta and gamma using wavelet transform. Classification of emotions was done using 5 fold cross validation with K-NN & LDA classifier, achieving an average accuracy of 79.14% and individually 91% on disgust, 60% surprise, 88% on happy, 73.75% fear and 87.5% on neutral [29].

Frantzidis, C et al (2010) collected the EEG signal from 28 subjects using the IAPS dataset images for invoking emotions. These emotions were categorised into four classes. Feature extracted was ERP using three electrodes such as Fz, Cz and Pz for classifying emotions. This classification was performed using MD and SVM in various kinds of kernels such as polynomial, linear and Radial Basis Function. The average accuracy achieved by using MD was 79.46% and using SVM was 81.25% [30].

Khosrowabadi, R et al (2010) gathered EEG signals using IAPS images for invoking emotions from 26 subjects over eight electrodes. The features extracted were the magnitude of squared coherence of the EEG signals and boundaries of these features were then extracted using self organizing map. Emotions were classified into four states such as calm, sad, happy and fear using k-NN classifier giving an accuracy of 84.5% [31].

Yuen, C.T et al. (2010) acquired EEG data using 64 electrodes from three male and female subjects using audio visual stimuli for invoking emotions. Six statistical features were extracted from EEG signal. Classification of emotions was done into five states such as anger, sad, surprise, happy, and neutral using back propagation neural network classifier, achieving 95% accuracy [32].

Petrantonakis, P.C et al. (2010) gathered EEG signal from 16 subjects using three electrodes, such as Fp1, Fp2 and a combined channel of F3 and F4, using Mirror Neuron system for emotion elicitation in the subjects. Classification of emotions was done into six states such as happiness, surprise, anger, fear, disgust, and sadness. Higher order crossings (HOC) features were extracted to classify the emotions using four classifiers namely QDA, k-NN, MD and SVM. The EEG data acquired from single elecrode and from combined electrodes resulted in best accuracy of 62.3% using QDA and 83.33% using SVM respectively [33].

Xu, H et al. (2012) gathered EEG data from 5 participants using enterface 06 database. Classification of emotions was done into three states such as Calm, Positive exciting and Negative exciting, using 54 electrodes. The extracted features were statistical, narrow-band, HOC, and wavelet entropy. K-NN Classifier was used giving an average accuracy of 90.77% [34].

Singh, M. et al. (2013) gathered EEG Data using enterface06 workshop database. Features extracted were PSD, STFT and ERP for classifying emotions into two classes using ANN and Naïve Bayes classifiers [35] [36] [37] [38].

Jatupaiboon, N. et al. (2013) acquired EEG data from 11 subjects by using emotion evoking images from GAPED [39], using 14 electrodes for classifying emotions into two classes. EEG Data was divided into spectral bands: Delta band, Theta band, Alpha band, Beta band and Gamma band. Feature extracted was power spectrum for each band giving an accuracy of 85.41% using 10 -fold cross validation with Support Vector Machine classifier [40].

Singh, M et al. (2014) acquired EEG Data from 3 subjects using emotion evoking pictures from IAPS , using three electrodes such as Cz, F3 and F4. Features extracted were ERP and average of ERP for classifying emotions into two classes along valence axis, using SVM [41] [42] .

Zheng, W.L et al. (2014) collected EEG Data from three male and female subject using movie clip as emotion evoking stimuli, using 62-channel electrode. A new method was developed called hidden markov model (HMM) to classify emotions accurately. Features extracted was differential entropy for the classification of emotions into two states by using K-NN , SVM ,GELM , DBN (Deep Belief Networks) and DBN-HMM classifier, giving an average accuracies of 69.66%, 84.08%, 85.67%, 86.91% and 87.62% respectively. Better results were achieved using the DBN and DBN-HMM methods compared to other methods [43].

CHAPTER 3

DATA COLLECTION

3.1 EEG Data Collection using BIOPAC

The EEG data has been acquired, from three subjects, by stimulating the subjects with emotion evoking images from IAPS dataset provided by NIMH Center at University of Florida. These images from the IAPS are quantified along three axes: Valence, Arousal and Dominance [44]. The images belonging to HVLA and LVHA are shown to the subjects [45] [46]. Images shown to each of the subjects are of different types such as nature, baby, love, snake, grave etc. Total 80 images are used to evoke emotions. The subject is asked to sit still while acquiring data. He is not allowed to yawn, and to blink his eyes, during the acquisition of EEG data.The epoch time is of 2.5 seconds. An image from LVHA is shown for 1 second followed by a plus symbol for 1.5 seconds to give comfort to subject. Then next image related to HVLA is shown to the subject for 1 second followed by plus symbol for 1.5 seconds and vice versa. This EEG data has been collected by placing a 20 electrode cap on the subject's head as per the 10-20 system. EEG gel is filled in the electrodes to create contact between electrodes and scalp. With perfect synchronization between the data acquisition system and the presentation system, EEG data has been collected from the subjects.

The acquired raw EEG signal from one of the participants is shown in Figure 1.9.

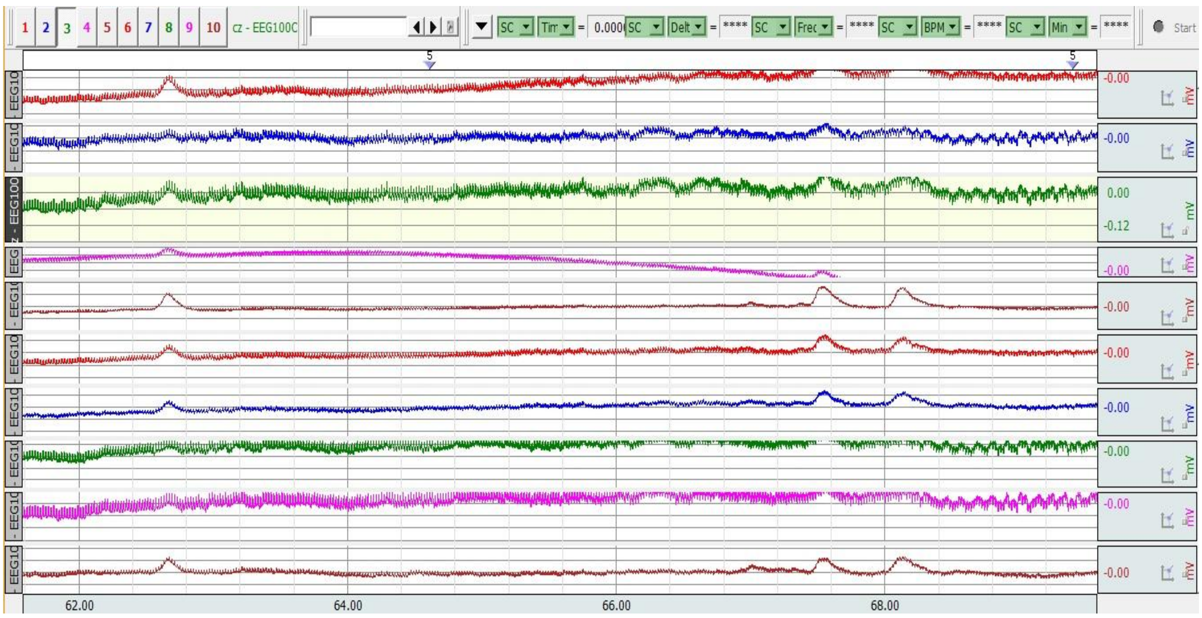

Figure 3.1: Acquired raw EEG signal in Acq 4.2 Software

Frontal electrodes namely F1, F2, F3, F4 and Fz, a parietal electrode Pz and a central electrode Cz are chosen for EEG signal processing and analysis. The EEG signals are acquired at a sampling rate of 500 samples per second.

3.1.1 Hardware

The BIOPAC data acquisition unit MP150 interfaced with 20 electrode EEG cap is used to acquire EEG signals. The system consists of EEG amplifiers and earlobes attached to the subject. With the help of a syringe, EEG gel is to be filled in the electrodes. The impedance level is maintained below10 Kilo-ohm. The MP150 system comprises of 10 bio-amplifiers on to which 10 EEG electrodes are connected to acquire the data in unipolar mode. 20 electrodes can be connected to acquire data in bipolar mode. In this dissertation, the EEG data is acquired in unipolar mode. The acquired EEG signals are shown on the computer system loaded with ACQ 4.2 Software provided by BIOPAC [47] .

3.1.2 Pre-processing of EEG Signals using ACQ 4.2 Software

Signal pre-processing is done for achieving better classification of emotions. After acquiring EEG signal, it is then signal conditioned using the ACQ Software 4.2. Firstly, a low pass filter, with a cut off frequency of 40 Hz, is applied on the EEG signal to bring the signal in the range of 0.5 Hz to 40 Hz followed by a high pass filter with a cut off frequency of 0.5Hz. The power noise interference is removed by using a comb band stop filter with a notch frequency of 50Hz. Figure 3.2 shows the pre-processed EEG signal.

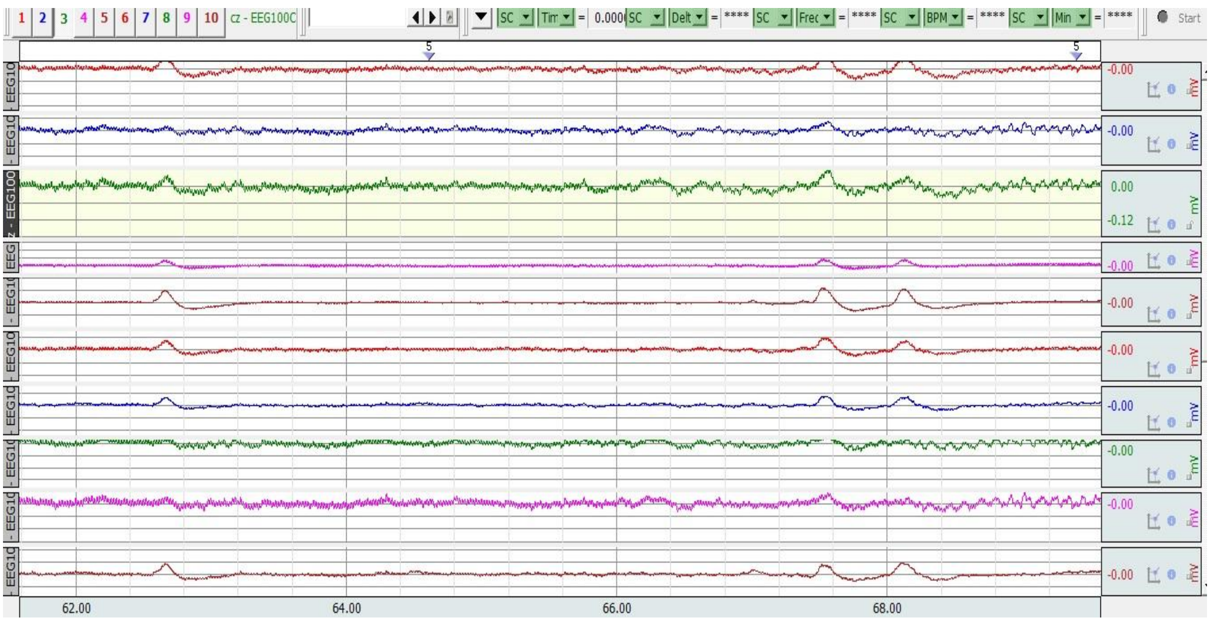

Figure 3.2: Pre-processed EEG Signal in Acq 4.2 Software

3.2 EEG Data Collection using enterface 06

Raw EEG signals are taken from the database of enterface workshop in the year 2006, referred to as the Enterface 06 database, developed by Savran et al. [48]. In this workshop, the data was acquired from five subjects, all are male and right handed, in three sessions. In each session the participant was shown 30 blocks of images. Each block pertains to one class of emotion such as POS (exciting positive), NEG (exciting negative) and CALM and contains five images.

Calm: Arousal < 4;   4 < valence < 6

POS: Valence > 6.8; Var (Valence) < 2;   Arousal > 5

NEG: Valence < 3;   Arousal > 5

Each of the five images is shown for 2.5 seconds each, thus 12.5 seconds for each block of image. In between the two blocks, a black screen is shown for 10 seconds. After this, the subject needs to self-assess his emotions. This self-assessment is done because emotions are subjective and are dependent on previous experiences. The researchers used images from the IAPS for evoking emotions in the subjects. The data had been collected by using a Biosemi Active 2 device with 64 electrodes in BDF format (Biosemi Data Format) at a sampling rate of 1024 Hz but the first session of subject 1 was recorded at 256 Hz and the images were shown in a random order [49].

Data which is downloaded from enterface website has two files which are listed below:

PARTA_IAPS_SESB_EEG_fNIRS_DDMMAAAA.bdf
PARTA_IAPS_SESB_EEG_fNIRS_DDMMAAAA.mrk

MRK file indicates time of start and termination of an emotion stimulus to the participant.

Here A is the subject number (1-5), B is the session number (1-3) and DDMMAAAA represents the date of recording.

Also, a folder labelled as Common Data in the downloaded data, contains the following files:

• IAPS_Images_EEG_fNIRS.txt containing three columns, one per session, with the names of the IAPS images used in this research.

• IAPS_Eval_Valence_EEG_fNIRS.txt and IAPS_Eval_Arousal_EEG_fNIRS.txt containing three columns listing the valence and arousal value for each picture.

• IAPS_Classes_EEG_fNIRS.txt – It contains three columns labelling the associated classes for each block of pictures as “Calm”, “Pos” or “Neg”.

In this dissertation, we have classified the emotions of 8 subjects i.e. three subjects using electrodes and BIOPAC data acquisition unit and five subjects using enterface database into two classes: HVLA and LVHA. Also, here **Calm represents HVLA and Neg represents LVHA**. Five frontal electrodes namely F1, F2, F3, F4 and Fz, a parietal electrode Pz and a central electrode Cz are considered for data processing and analysis.

3.2.1 EDF Browser

It is a free, open source, multi-platform, universal viewer and toolbox intended for time series storage files like EEG, EMG, ECG, Bio-Impedance, etc. It supports file formats such as EDF, EDF+, BDF and BDF+. As our EEG Data was in BDF format, so, with the help of this software we could do our further data processing and analysis. Figure 2.1 shows the EEG Signal in EDF Browser.

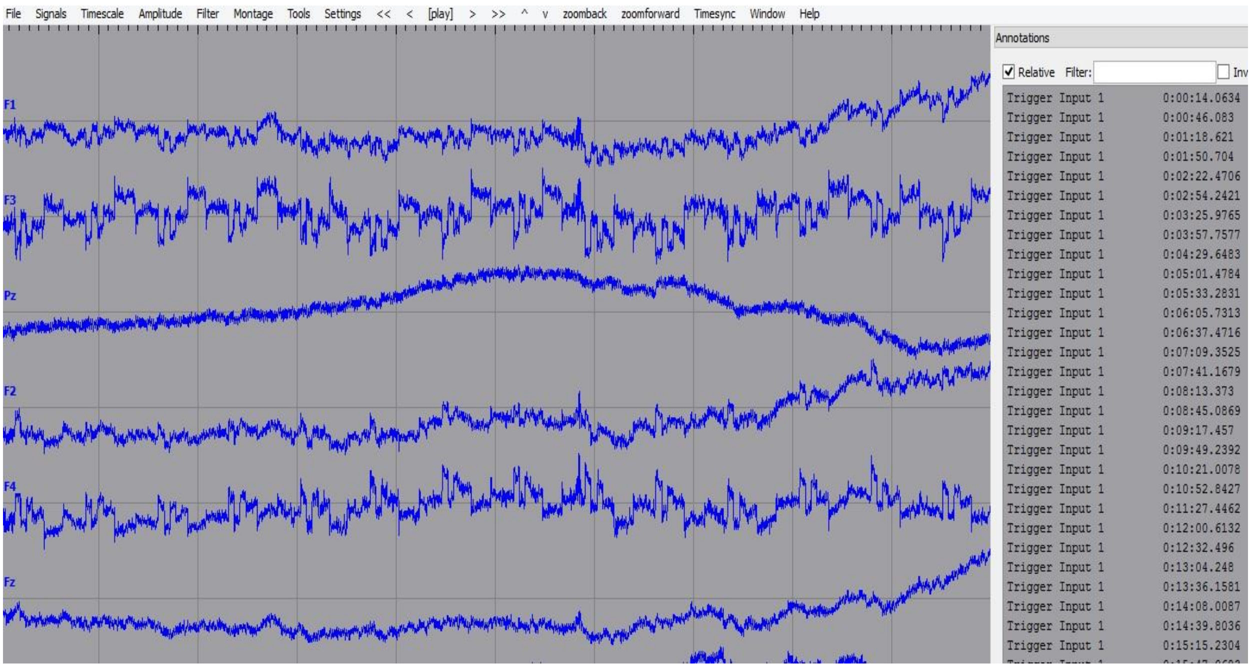

Figure 3.3: EEG Signal in EDF Browser

3.2.2 Pre-processing of EEG Signal using EDF Browser

The collected EEG signal was signal conditioned using the EDF Browser. Firstly, a Butterworth Band pass filter of 0.5 Hz to 40 Hz of order 4 i.e. slope roll-off 12 dB/octave was applied on the EEG Signals to bring the signal in the desired range, followed by a Resonator Notch filter, with a frequency of 50 Hz and notch Q-factor of 20, to remove the power noise interference in the signal. Figure 3.4 shows the pre-processed EEG Signal in EDF Browser.

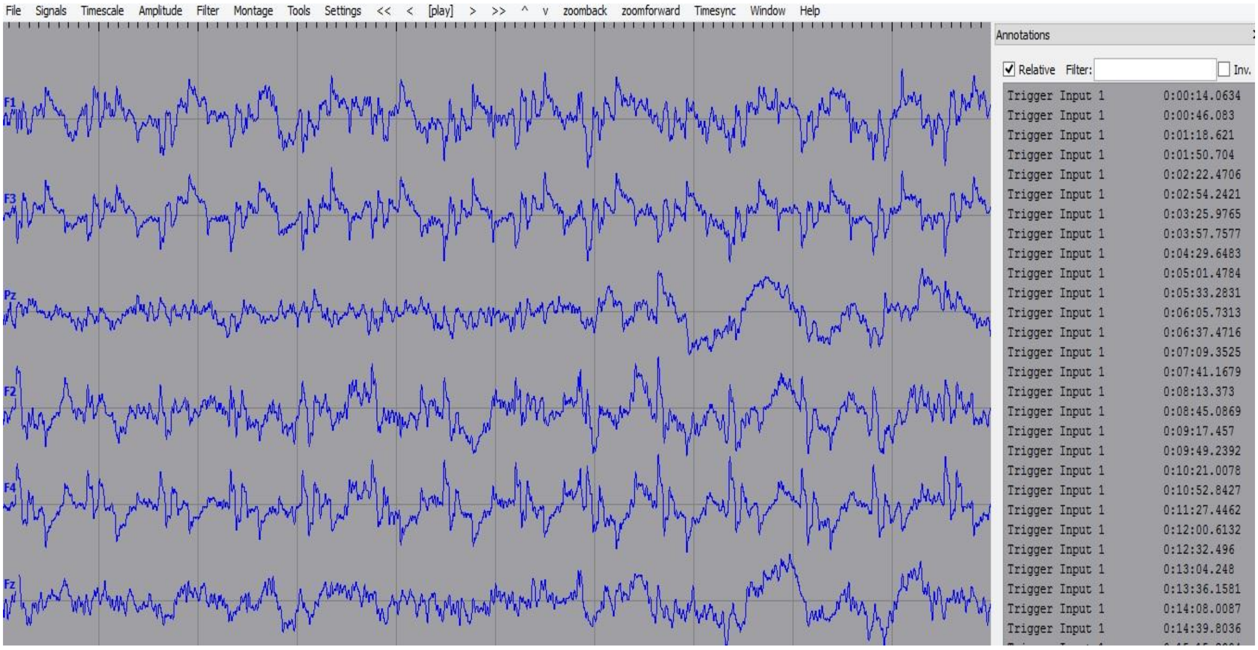

Figure 3.4: Pre-processed EEG Signal in EDF Browser

CHAPTER 4

METHODOLOGY

The steps for classification of emotions in this research are shown in Figure 4.1.

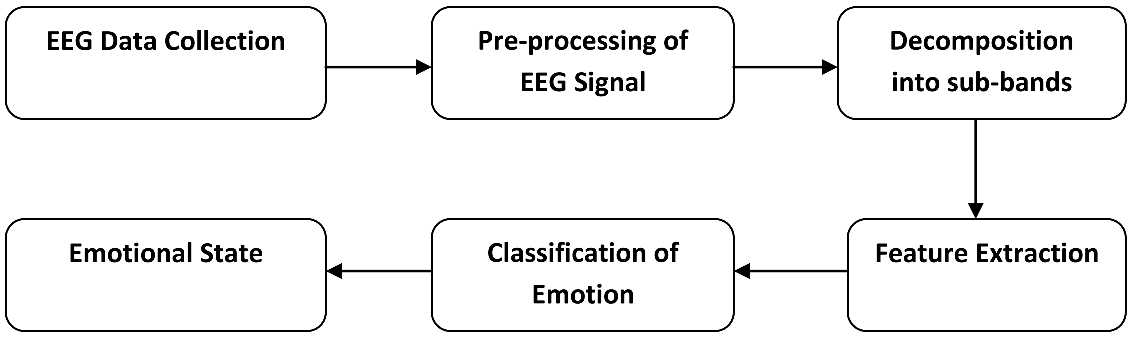

Figure 4.1: Steps for Emotion Classification

4.1 Feature Extraction

A band pass IIR Butterworth filter was applied on the averaged EEG signal for each of the seven channels F1, F2, F3, F4, Fz, Cz and Pz to keep only alpha band (8-12 Hz) frequencies and beta band (13–30 Hz) frequencies to comprehend the relationship between prefrontal cortical activation and inactivation. Also an increased alpha band activity along with a decreased activity in beta band shows a cortical inactivation whereas the opposite shows active prefrontal cortex [50]. The reason to choose alpha and beta bands are: They are more suitable for emotion recognition tasks [51]; The effect of eye movement or blinking is more prominent upto 4 Hz; heart-functioning can create artifacts around 1.2 Hz, and muscle artifacts have an effect on EEG signal above 30 Hz. Also, power lines cause non-physiological artifacts above 30 Hz (50-60 Hz). So by extracting alpha and beta bands from the EEG spectrum, much of the noise interference was removed [52]. The averaged and filtered EEG signals were subjected to a zero-mean process by subtracting their mean value in order to apply the Feature extraction method. This process is also called Removal of Bessel Value.

4.1.1 Higher Order Crossings (HOC) Analysis

In this dissertation we have extracted features called Higher Order Crossings (HOC). The oscillating nature of a finite zero-mean series $Z_t, t = 1,...N$ about the zero level can be expressed by zero-crossings count. When a filter is applied on a time sequence, it changes its oscillation nature and so the no. of zero crossings counts and the more distinct the oscillation is, the higher the expected no. of zero-crossings is and vice versa. Thus repeatedly applying a filter on a time series and counting the no. of zero-crossings, each time the filtering order k increases, the resulting sequence of zero-crossings counts is called Higher Order Crossings (HOC) [53]. This relation in the oscillatory pattern can be understood using correlation technique. Both zero-crossings counts and first order auto correlation are the measures of oscillation. And the relation between zero-crossing rates and auto correlation imply a connection between zero-crossings and spectrum, such as EEG spectrum and thus helps in finding out the emotion expression in the brain [54].

Let Z_1, Z_{2},... Z_N be a zero mean stationary time series, the zero-crossing count in discrete time is defined as the no. of symbol changes in the related binary time series.

$$X_t = \begin{cases} 1 \ if \ Z_t \ \geq 0 \\ 0 \ if \ Z_t \ \leq 0 \end{cases} \tag{4.1}$$

The no. of zero-crossings, denoted by D, is defined in terms of X_t,

$$\sum_{t=2}^{N}[X_t - X_{t-1}]^2, \ 0 \leq D \leq N - 1 \tag{4.2}$$

HOC combines ZC counts and linear operations and the difference operator is a linear high-pass filter,

$$\nabla Z_t \equiv Z_t - Z_{t-1} \tag{4.3}$$

Advantage of using HOC is that zero-crossings count is not only referred to initial signal but also to the signals that contains the output of high-pass filtering of the initial signal. As a result, the dominant frequency rule is applied to a set of sub-bands of the initial signal, finding out a respective set of dominant frequencies.

4.2 Classification

A classifier divides the EEG data into different classes of emotions. It gives the relation between the extracted features and emotions of the subjects. We have used two classifiers namely SVM and k-NN using WEKA to classify the emotions into two classes: HVLA i.e. “Calm” and LVHA i.e. “Negative Exciting”.

4.2.1 The WEKA Workbench

WEKA (The Waikato Environment for Knowledge Analysis) is open source software which comprises of machine learning methods and data pre-processing tools, useful for machine learning and data mining. The workbench includes algorithms for classification, regression, clustering, association rule mining, visualization and attribute selection [55]. It is suitable to develop new machine learning schemes. The various machine learning algorithms are: Decision trees, SVMs, multi-layer perceptrons, logistic regression, Bayes networks and lazy learning methods like IB1, IBk, KStar and lazy Bayesian rules [56] .

4.2.2 Support Vector Machine Classifier

In WEKA, Sequential Minimal Optimization (SMO) is used as classifer which is a fast algorithm used to train SVMs to solve very large quadratic programming (QP) problem quickly. SMO decomposes overall QP query into QP sub-queries, using Osuna's theorem. SMO has better scaling properties for difficult SVM problems [57].

In SVM, training vectors are plotted in high-dimensional feature space, and each vector is labelled with its class. A hyperplane is drawn between these training vectors to maximize the distance between different classes. This hyperplane is determined with the help of kernel function, given as an input to classifier. The classification task is to find out which side of the hyperplane the testing vectors lie. The kernel function can be linear, polynomial, radial basis, or sigmoid. In this dissertation we have used polynomial kernel function. The shape of the hyperplane is dependent on kernel function, though many experiments select the polynomial kernel function as the best method [58]. Figure 2.3 shows the optimal hyperplane using a SVM.

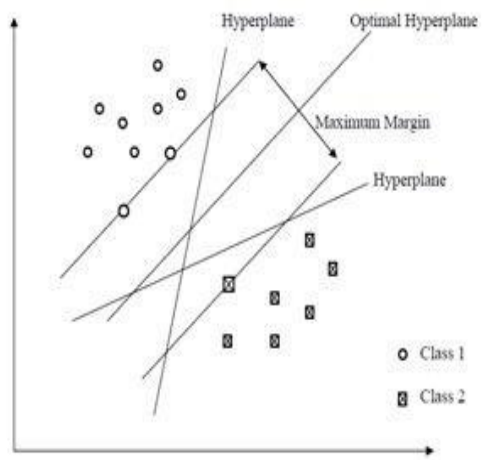

Figure 4.2: Optimal Hyperplane using SVM

SVM guarantees the best kernel function which maximizes margin between two classes. Geometrically, margin defines shortest possible distance within the nearest data points to a point on hyperplane. SVM's reason for helping in finding the maximum margin hyperplanes out of infinite hyperplanes as solution is that it has the highest generalization ability. It gives the best classification accuracy on the training data, and can ensure the correct classification of the future data.

4.2.3 k-Nearest Neighbour Classifier

In WEKA, IBk is a lazy learning method used as a k-NN classifier k-NN classifier compares a newly labelled sample (testing data) with the training data and gives the decision accordingly. Training data set includes classes. For a given values in the data set, k-NN finds the k i.e. closest neighbourhood in training data set. Usually Euclidean distance gives the distance measure that is only relevant to variables that are continuous. In this dissertation, we have used Euclidean distance as the algorithm. Then a class is assigned that frequently appears in its neighbourhood [59]. The algorithm for k-NN classifier is given as follows:

1. The k-NN classification first step is to give the training data set which is the combination of input and target variables.

2. The second step is testing in which comparison is done between the test data which consists of input variables and the set of references.

3. K-NN goes ahead with k number of patterns, the class is determined by the value of distance and by taking into consideration the nearest neighbours.

4. Majority voting scheme is used for each instance where class gets one vote in the neighbourhood samples [60].

4.2.4 Cross Validation

It is a modular method of validation used for investigating that how the results of a machine learning algorithm will respond to an independent data set. It is mainly utilised for prediction i.e. when one wants to assess how precisely a predictive model will perform. In a prediction related query, model is generally provided with a dataset of known data on which training is performed i.e. the training dataset, and a dataset of unknown data on which model is tested i.e. the testing dataset [61]. Purpose of cross validation is to define a dataset to "test" the model in training phase i.e. the validation dataset, so as to avoid problems like overfitting i.e. when a model is very complex or gives a poor predictive performance.

N-Fold Cross-Validation

The dataset is arbitrarily divided into N equal sized subsets. Of these N subsets, a single subset is taken as validation data for testing the model, and the left over N − 1 subsets are utilised as training data. Cross-validation is then repeated N times, with each of the N subsets used exactly once as validation data. The N results from the folds are then averaged to produce a single evaluation. The advantage is that all subsets are used for both training and validation, and each subset is used for validation exactly once. In this dissertation we have divided the entire dataset as 75% training dataset and 25% testing dataset. Then 10-Fold Cross Validation is applied on the training dataset using WEKA. **Stratified cross-validation** is chosen by default in WEKA, in which the subsets are selected such that mean response value is roughly equal in all the subsets.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Results

The extracted data is classified into two classes: HVLA and LVHA using SVM and k-NN. Higher Order Crossings (HOC) as features are extracted to find out the accuracy of EEG data. WEKA Software is used for classifying the emotions. HOCs are calculated for order of high pass filter as ‘k’ from 1 to 10 on following EEG channels namely F1, F2, F3, F4, Fz, Pz and Cz.

HOCs are extracted in following ways:

- Five participants Session 1 EEG Data from enterface 06 and other three subjects EEG Data using BIOPAC.
- Five participants Session 2 EEG Data from enterface 06 and other three subjects EEG Data using BIOPAC.
- Five participants Session 3 EEG Data from enterface 06 and other three subjects EEG Data using BIOPAC.
- Five participants Session1, Session 2, Session 3 EEG Data from enterface 06.

Firstly for any of the above following ways, the entire dataset of extracted HOC features is divided into 75% training set and 25% testing set. Then the classifier model has been trained using the training set and applying cross validation technique on it. Classification Accuracy was calculated using SMO and IBK in WEKA software. Then the model is tested on unknown data i.e. the testing set and the classification accuracy was calculated to know how good or bad the predictive performance is i.e. how much accurately the emotions are classified.

HOCs are extracted for first order of high pass filter i.e. $k = 1$ then for first and second order combined i.e. $k = 1$ to 2, similarly for first, second and third order combined i.e. $k = 1$ to 3 and so on for $k = 1$ to 10. Using these HOCs features, emotions are classified into two classes namely CALM (HVLA) and NEG (LVHA).

Below Table 1 depicts the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using SVM for different orders of the filter for 8 Subjects with Session 2.

Table 5.1: Classifier Accuracy on 8 Subjects with Session 1 using SVM

HOC ORDER K	TRAINING SET INSTANCES	CROSS VALIDATION ON TRAINING SET		CROSS VALIDATION ON TRAINING SET ACCURACY IN %	SUPPLIED TEST SET INSTANCES	SUPPLIED TEST SET		SUPPLIED TEST SET ACCURACY IN %
		CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES			CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	
1	74	39	35	52.7027	27	14	13	51.8519
2	139	70	69	50.3597	45	29	16	60.4444
3	216	118	98	54.6296	74	46	28	62.1622
4	307	175	132	58.0033	89	61	28	68.5393
5	403	250	153	62.0347	99	60	39	60.6061
6	455	342	169	62.8571	113	77	36	63.3987
7	535	402	225	57.9439	133	87	46	68.9266
8	614	460	220	64.1694	153	91	62	60.7379
9	694	386	308	55.6196	187	124	63	66.3102
10	788	429	359	54.4416	203	141	62	69.4581
AVERAGE ACCURACY OF CROSS VALIDATION ON TRAINING SET IN %				**57.27616**	**SUPPLIED TEST SET ACCURACY IN %**			**64.24354**

Average Accuracy of Cross Validation on Training Set for 8 Subjects with Session 1 using SVM is 57.27 % while Average Accuracy on the Supplied Test Set is 64.24%

Below Figure 5.1 shows the graph representing the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using SVM on the eight subjects considering Session 1 EEG Data of the five subjects from enterface06 database and the three subjects using BIOPAC.

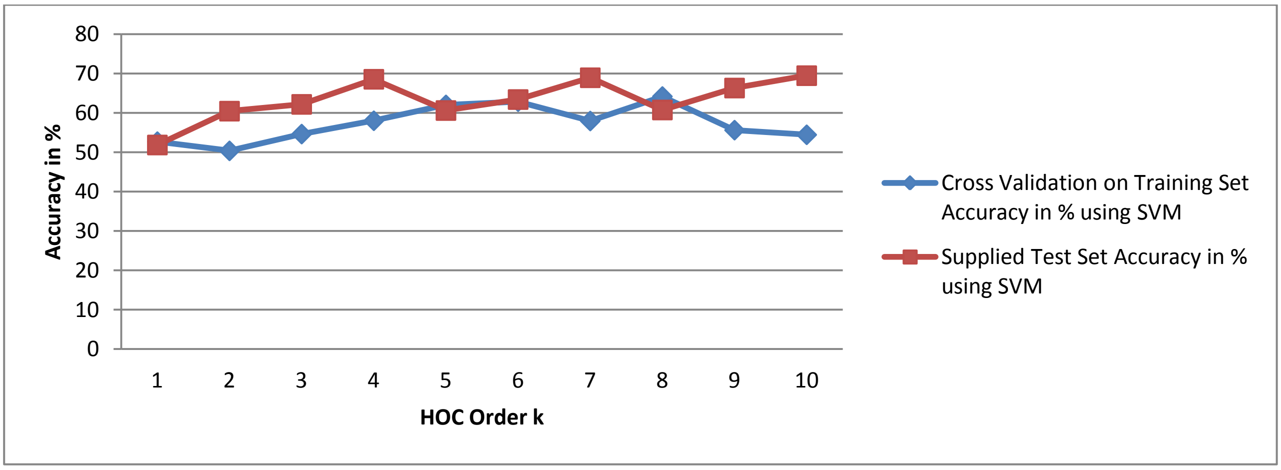

Figure 5.1: Classifier Accuracy on 8 Subjects with Session 1 using SVM

Below Table 5.2 depicts the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using k-NN for different orders of the filter.

Table 5.2: Classifier Accuracy on 8 Subjects with Session 1 using k-NN

HOC ORDER K	TRAINING SET INSTANCES	CROSS VALIDATION ON TRAINING SET		CROSS VALIDATION ON TRAINING SET ACCURACY IN %	SUPPLIED TEST SET INSTANCES	SUPPLIED TEST SET		SUPPLIED TEST SET ACCURACY IN %
		CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES			CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	
1	74	41	33	55.4054	27	19	8	70.3704
2	139	84	55	60.4316	45	35	10	77.7778
3	216	124	92	57.4074	74	53	21	71.6216
4	307	201	106	65.4723	89	60	29	67.4157
5	403	252	151	62.531	99	76	23	76.7677
6	455	285	170	62.6374	113	81	32	71.8954
7	535	341	194	63.7383	133	105	28	79.661
8	614	416	198	67.7524	153	115	38	75.3883
9	694	477	217	68.732	187	157	30	83.9572
10	788	537	251	68.1472	203	168	35	82.7586
AVERAGE ACCURACY OF CROSS VALIDATION ON TRAINING SET IN %				**63.2255**	**SUPPLIED TEST SET ACCURACY IN %**			**75.76137**

Average Accuracy of Cross Validation on Training Set for 8 Subjects with Session 1 using k-NN is 63.22 % while Average Accuracy on the Supplied Test Set is 75.76%.

Below Figure 5.2 shows the graph representing the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using k-NN on the eight subjects considering Session 1 EEG Data of the five subjects from enterface06 database and the three subjects using BIOPAC.

Figure 5.2: Classifier Accuracy on 8 Subjects with Session 1 using k-NN

Below Figure 5.3 compares the accuracy of SVM & k-NN Classifiers for 8 Subjects with Session 1.

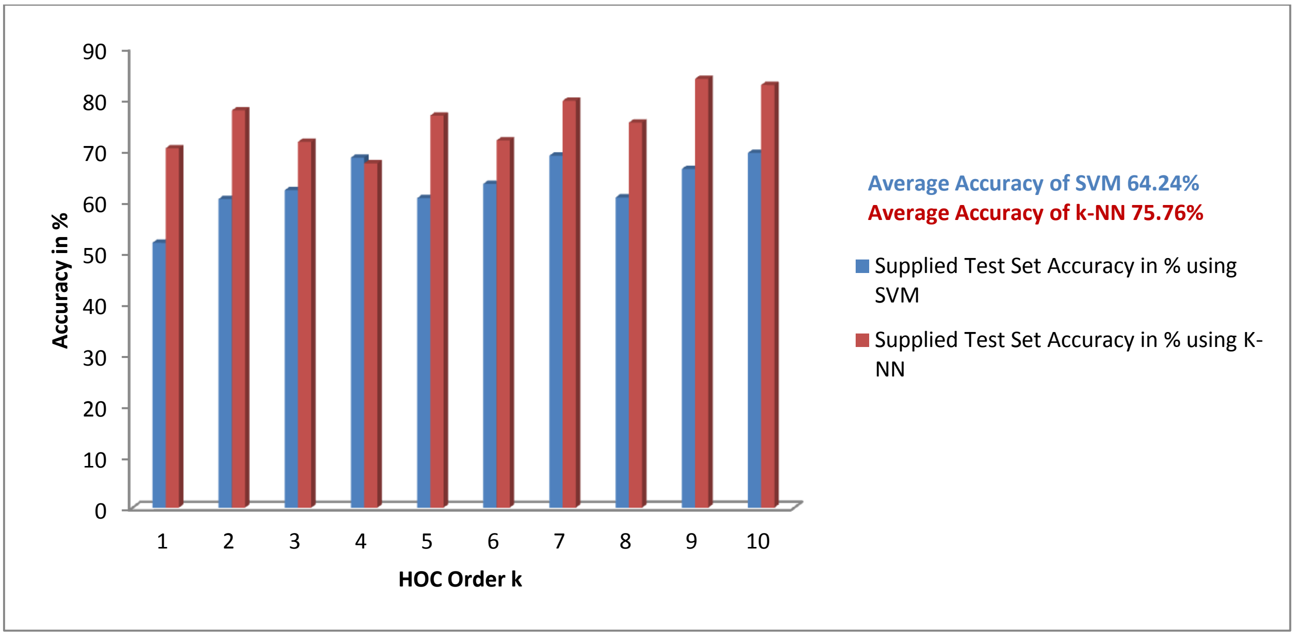

Figure 5.3: Comparison of Accuracy of SVM & k-NN on 8 Subjects with Session 1

Below Table 5.3 depicts the accuracy of Cross Validation on Training Set and Supplied Test Set accuracy using SVM for different orders of the filter for 8 Subjects with Session 2.

Table 5.3: Classifier Accuracy on 8 Subjects with Session 2 using SVM

HOC ORDER K	TRAINING SET INSTANCES	CROSS VALIDATION ON TRAINING SET		CROSS VALIDATION ON TRAINING SET ACCURACY IN %	SUPPLIED TEST SET INSTANCES	SUPPLIED TEST SET		SUPPLIED TEST SET ACCURACY IN %
		CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES			CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	
1	74	42	32	56.7568	21	12	9	57.1429
2	128	69	59	53.9063	44	22	22	50
3	188	100	88	53.1915	76	39	37	51.3157
4	273	139	134	50.9158	87	46	41	52.8735
5	348	184	164	52.8735	112	59	53	52.6786
6	455	227	209	52.0642	123	62	61	50.4065
7	506	265	241	52.3715	168	90	78	53.5714
8	574	288	286	50.1742	183	104	79	56.8306
9	635	339	296	53.3858	221	119	102	53.8462
10	711	397	314	55.8368	230	124	106	53.913
AVERAGE ACCURACY OF CROSS VALIDATION ON TRAINING SET IN %				**53.14764**	**SUPPLIED TEST SET ACCURACY IN %**			**53.27584**

Average Accuracy of Cross Validation on Training Set for 8 Subjects with Session 1 using SVM is 53.14 % while Average Accuracy on the Supplied Test Set is 53.27%.

Below Figure 5.4 shows the graph representing the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using SVM on the eight subjects considering Session 2 EEG Data of the five subjects from enterface06 database and the three subjects using BIOPAC.

Figure 5.4: Classifier Accuracy on 8 Subjects with Session 2 using SVM

Below Table 5.4 depicts the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using k-NN for different orders of the filter for 8 Subjects with Session 2.

Table 5.4: Classifier Accuracy on 8 Subjects with Session 2 using k-NN

HOC ORDER K	TRAINING SET INSTANCES	CROSS VALIDATION ON TRAINING SET		CROSS VALIDATION ON TRAINING SET ACCURACY IN %	SUPPLIED TEST SET INSTANCES	SUPPLIED TEST SET		SUPPLIED TEST SET ACCURACY IN %
		CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES			CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	
1	74	34	40	45.9459	21	12	9	57.1429
2	128	81	47	63.2813	44	30	14	68.1818
3	188	121	67	64.3617	76	57	19	75
4	273	167	106	61.1722	87	62	35	71.2644
5	348	210	138	60.3448	112	85	27	75.8928
6	455	345	110	75.8241	123	107	16	86.9919
7	506	350	156	70.1581	168	147	21	87.5
8	574	407	167	70.9059	183	131	52	71.5847
9	635	411	224	64.7244	221	170	51	76.9231
10	711	468	243	65.8227	230	193	37	83.913
AVERAGE ACCURACY OF CROSS VALIDATION ON TRAINING SET IN %				**64.25411**	**SUPPLIED TEST SET ACCURACY IN %**			**75.43946**

Average Accuracy of Cross Validation on Training Set for 8 Subjects with Session 1 using k-NN is 64.25 % while Average Accuracy on the Supplied Test Set is 75.44%.

Below Figure 5.5 shows the graph representing the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using k-NN on the eight subjects considering Session 2 EEG Data of the five subjects from enterface06 database and the three subjects using BIOPAC.

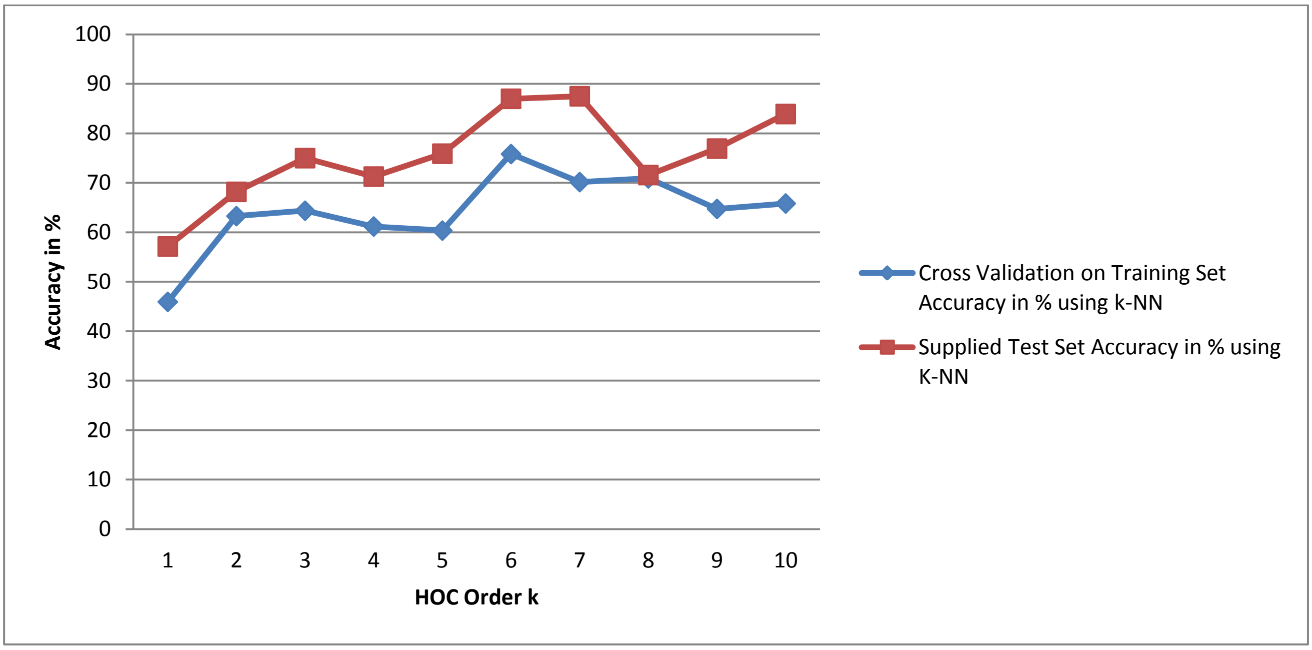

Figure 5.5: Classifier Accuracy on 8 Subjects with Session 2 using k-NN

Below Figure 5.6 compares the accuracy of SVM & k-NN Classifiers for 8 Subjects with Session 2.

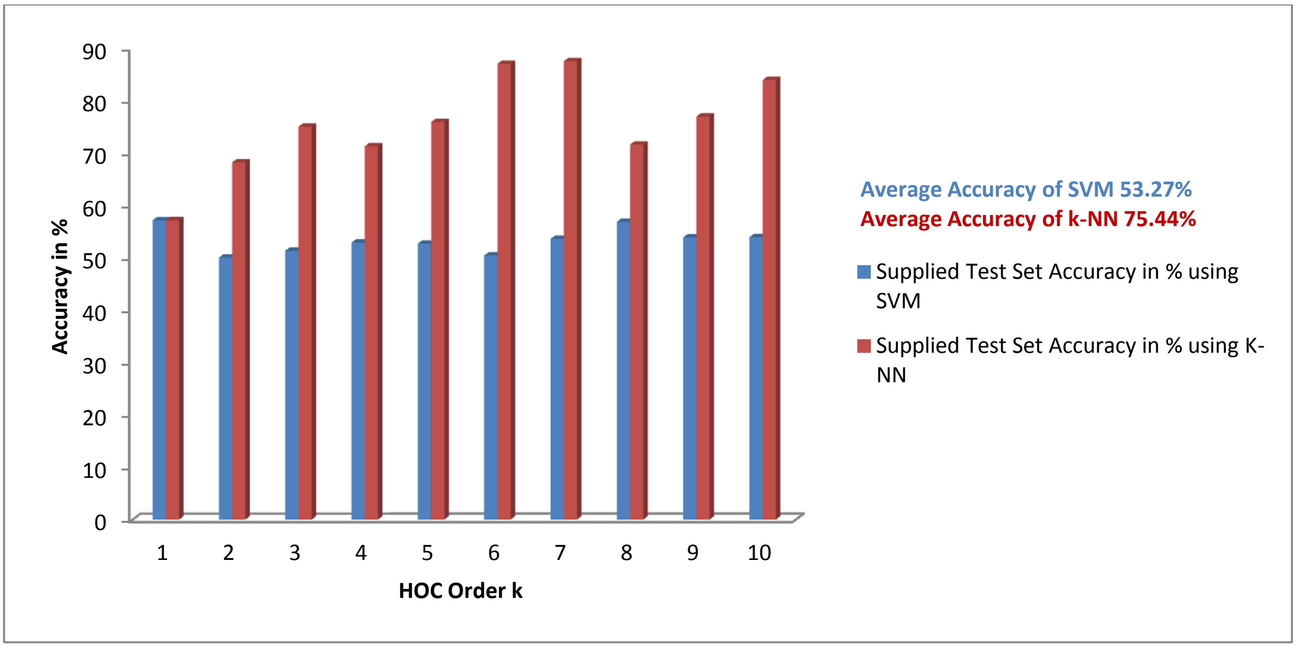

Figure 5.6: Comparison of Accuracy of SVM & k-NN on 8 Subjects with Session 2

Below Table 5.5 depicts the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using SVM for different orders of the filter for 8 Subjects with Session 3.

Table 5.5: Classifier Accuracy on 8 Subjects with Session 3 using SVM

HOC ORDER K	TRAINING SET INSTANCES	CROSS VALIDATION ON TRAINING SET		CROSS VALIDATION ON TRAINING SET ACCURACY IN %	SUPPLIED TEST SET INSTANCES	SUPPLIED TEST SET		SUPPLIED TEST SET ACCURACY IN %
		CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES			CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	
1	67	34	33	50.7463	23	14	9	60.8695
2	138	77	61	55.7971	46	24	22	52.1739
3	212	112	100	52.8302	64	38	26	59.375
4	282	165	117	58.5106	96	50	46	52.0833
5	347	186	161	52.8735	112	59	54	52.2124
6	410	207	203	52.0642	142	74	68	52.1127
7	482	244	238	50.6224	162	87	75	53.7037
8	574	303	252	54.5946	181	95	86	52.4862
9	626	315	311	53.3858	199	112	87	56.2814
10	668	348	320	52.0958	230	124	106	53.913
AVERAGE ACCURACY OF CROSS VALIDATION ON TRAINING SET IN %				**53.35205**	**SUPPLIED TEST SET ACCURACY IN %**			**54.52111**

Average Accuracy of Cross Validation on Training Set for 8 Subjects with Session 3 using SVM is 53.35 % while Average Accuracy on the Supplied Test Set is 54.52%.

Below Figure 5.7 shows the graph representing the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using SVM on the eight subjects considering Session 3 EEG Data of the five subjects from enterface06 database and the three subjects using BIOPAC.

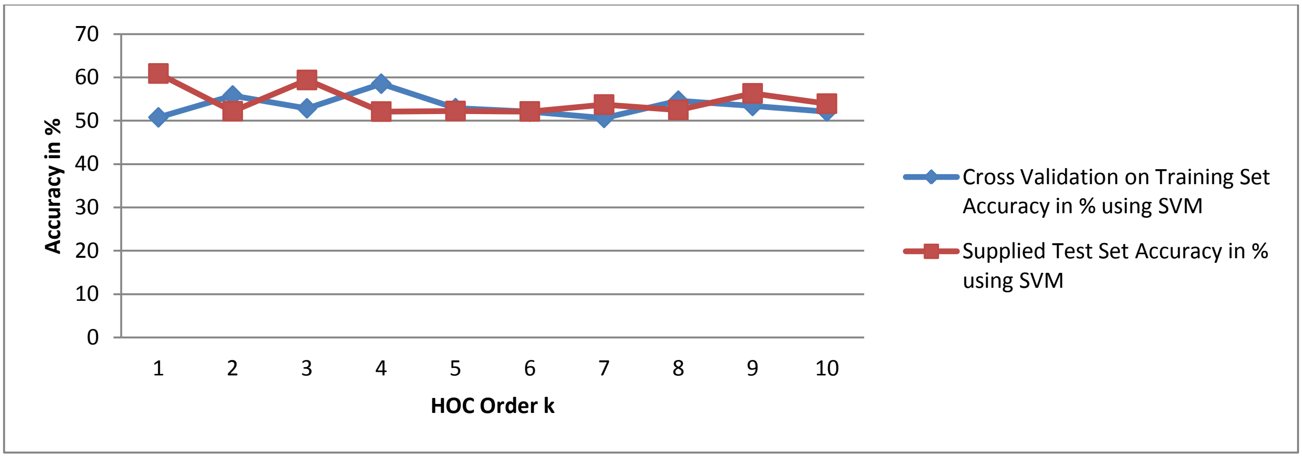

Figure 5.7: Classifier Accuracy on 8 Subjects with Session 3 using SVM

Below Table 5.6 depicts the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using k-NN for different orders of the filter for 8 Subjects with Session 3.

Table 5.6: Classifier Accuracy on 8 Subjects with Session 3 using k-NN

HOC ORDER K	TRAINING SET INSTANCES	CROSS VALIDATION ON TRAINING SET		CROSS VALIDATION ON TRAINING SET ACCURACY IN %	SUPPLIED TEST SET INSTANCES	SUPPLIED TEST SET		SUPPLIED TEST SET ACCURACY IN %
		CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES			CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	
1	67	34	33	50.7463	23	14	9	60.8695
2	138	80	58	57.971	46	30	16	65.2174
3	212	139	73	65.566	64	49	15	76.5625
4	282	171	111	60.6382	96	68	28	70.8333
5	347	227	120	65.4179	112	82	31	72.5664
6	410	264	146	64.3902	142	100	42	70.4225
7	482	325	157	67.4274	162	118	44	72.8395
8	574	352	203	63.4234	181	133	48	73.4807
9	626	410	216	65.4952	199	153	46	76.8844
10	668	463	205	69.3114	230	174	56	75.6521
AVERAGE ACCURACY OF CROSS VALIDATION ON TRAINING SET IN %				**63.0387**	**SUPPLIED TEST SET ACCURACY IN %**			**71.53283**

Average Accuracy of Cross Validation on Training Set for 8 Subjects with Session 3 using k-NN is 63.04 % while Average Accuracy on the Supplied Test Set is 71.53%.

Below Figure 5.8 shows the graph representing the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using k-NN on the eight subjects considering Session 3 EEG Data of the five subjects from enterface06 database and the three subjects using BIOPAC.

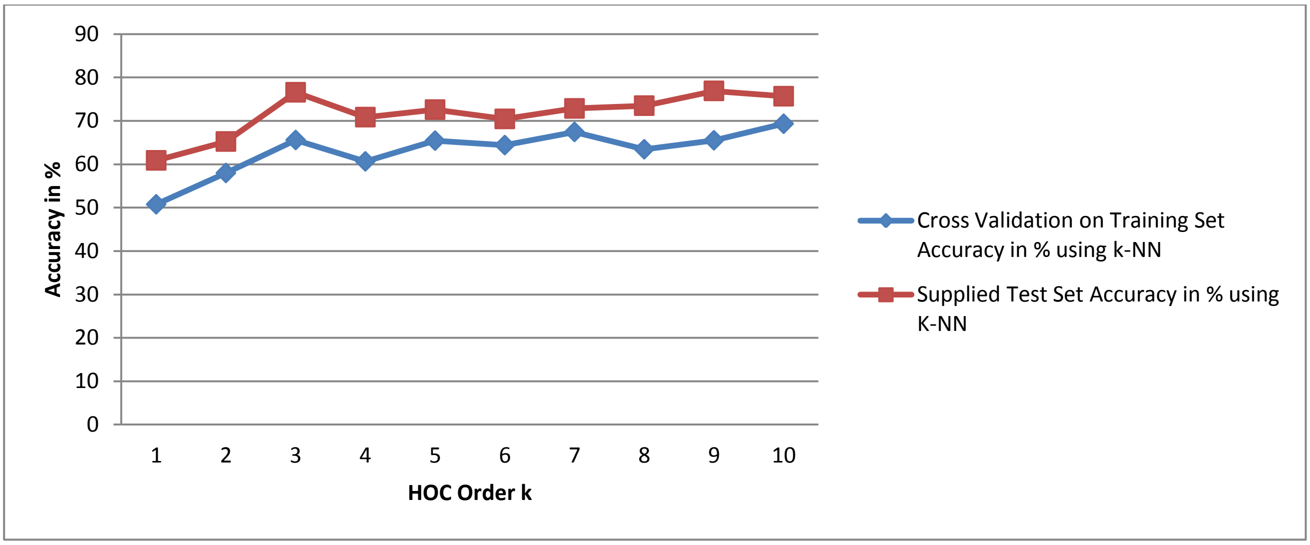

Figure 5.8: Classifier Accuracy on 8 Subjects with Session 3 using k-NN

Below Figure 5.9 compares the accuracy of SVM & k-NN Classifiers for 8 Subjects with Session 3.

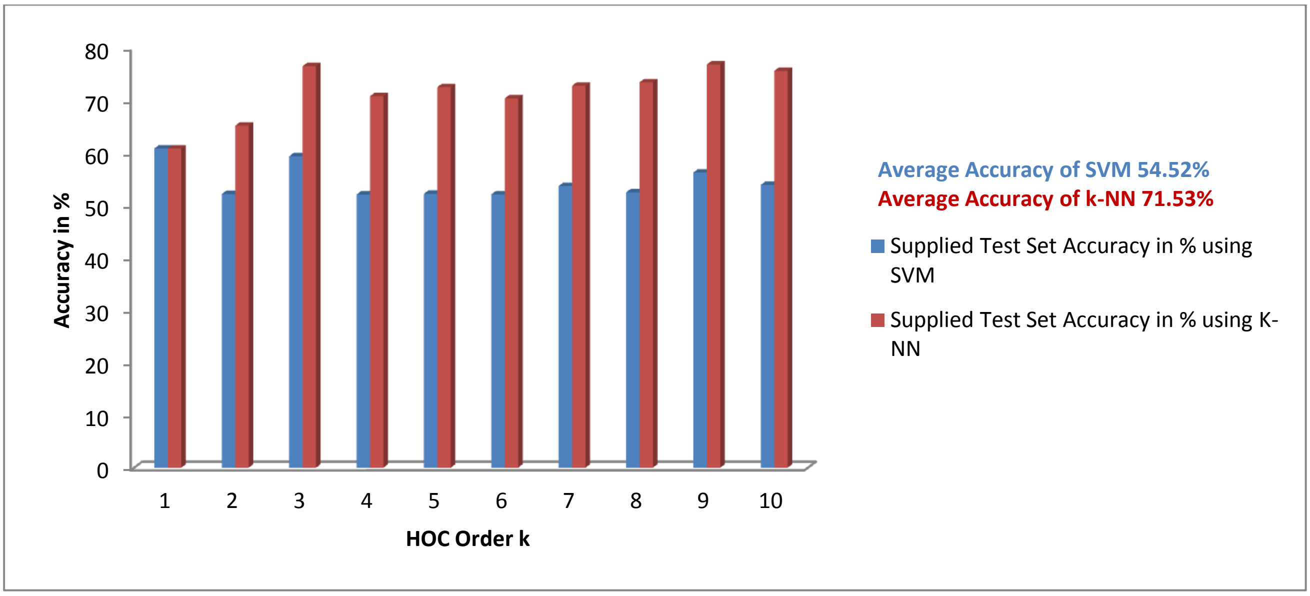

Figure 5.9: Comparison of Accuracy of SVM & k-NN on 5 Subjects with Session 3

Below Table 5.7 depicts the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using SVM for different orders of the filter for 5 Subjects with Session 1, Session 2 and Session 3 using enterface06 database.

Table 5.7: Classifier Accuracy on 5 Subjects with Session 1, Session 2 and Session 3 using SVM

HOC ORDER K	TRAINING SET INSTANCES	CROSS VALIDATION ON TRAINING SET		CROSS VALIDATION ON TRAINING SET ACCURACY IN %	SUPPLIED TEST SET INSTANCES	SUPPLIED TEST SET		SUPPLIED TEST SET ACCURACY IN %
		CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES			CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	
1	182	92	90	50.5495	45	24	21	53.3333
2	364	190	174	52.1978	91	47	44	51.6484
3	546	302	244	55.3114	136	79	57	58.0882
4	728	420	308	57.6923	182	107	75	58.7912
5	910	517	393	56.8132	227	123	104	54.185
6	1092	617	475	56.5018	273	159	114	58.2418
7	1309	734	575	56.0733	327	180	147	55.0459
8	1491	831	660	55.7344	373	215	158	57.6408
9	1673	939	734	56.1267	418	222	196	53.11
10	1855	1024	831	55.2022	464	263	201	56.681
AVERAGE ACCURACY OF CROSS VALIDATION ON TRAINING SET IN %				**55.22026**	**SUPPLIED TEST SET ACCURACY IN %**			**55.67656**

Average Accuracy of Cross Validation on Training Set for 5 Subjects with Session 1, Session 2 and Session 3 using SVM is 55.22 % while Average Accuracy on the Supplied Test Set is 55.68%.

Below Figure 5.10 shows the graph representing the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using SVM on the five subjects considering Session 1, Session 2 and Session 3 EEG Data of the five subjects from enterface06 database.

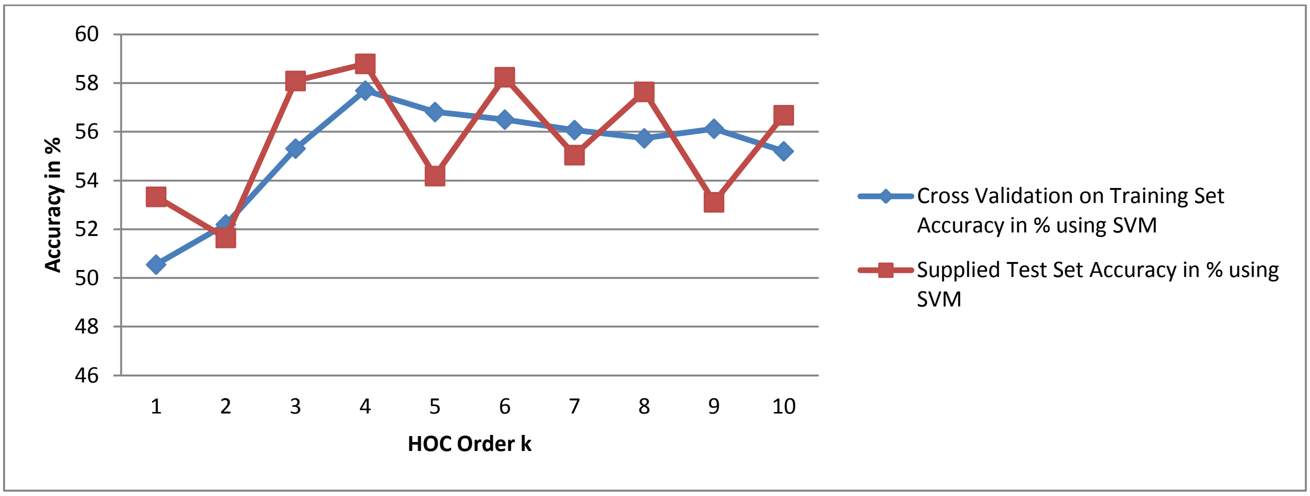

Figure 5.10: Classifier Accuracy on 5 Subjects with Session 1, Session 2 and Session 3 using SVM

Below Table 5.8 depicts the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using k-NN for different orders of the filter for 5 Subjects with Session 1, Session 2 and Session 3 using enterface06 database.

Table 5.8: Classifier Accuracy on 5 Subjects with Session 1, Session 2 and Session 3 using k-NN

HOC ORDER K	TRAINING SET INSTANCES	CROSS VALIDATION ON TRAINING SET		CROSS VALIDATION ON TRAINING SET ACCURACY IN %	SUPPLIED TEST SET INSTANCES	SUPPLIED TEST SET		SUPPLIED TEST SET ACCURACY IN %
		CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES			CORRECTLY CLASSIFIED INSTANCES	INCORRECTLY CLASSIFIED INSTANCES	
1	182	101	81	55.4945	45	30	15	66.6667
2	364	277	87	76.0989	91	63	28	69.2308
3	546	418	128	76.5568	136	103	33	75.7353
4	728	532	196	73.0769	182	138	44	75.8242
5	910	662	248	72.7473	227	180	47	79.2952
6	1092	771	321	70.6044	273	194	79	71.0623
7	1309	948	361	72.4217	327	243	84	74.3119
8	1491	1078	413	72.3005	373	255	118	68.3646
9	1673	1175	498	70.2331	418	294	124	70.3349
10	1855	1273	582	68.6253	464	309	155	66.5948
AVERAGE ACCURACY OF CROSS VALIDATION ON TRAINING SET IN %				**70.81594**	**SUPPLIED TEST SET ACCURACY IN %**			**71.74207**

Average Accuracy of Cross Validation on Training Set for 5 Subjects with Session 1, Session 2 and Session 3 using k-NN is 70.82% while Average Accuracy on the Supplied Test Set is 71.74

Below Figure 5.11 shows the graph representing the accuracy of Cross Validation on Training Set and the Supplied Test Set accuracy using k-NN on the five subjects considering Session 1, Session 2 and Session 3 EEG Data of the five subjects from enterface06 database.

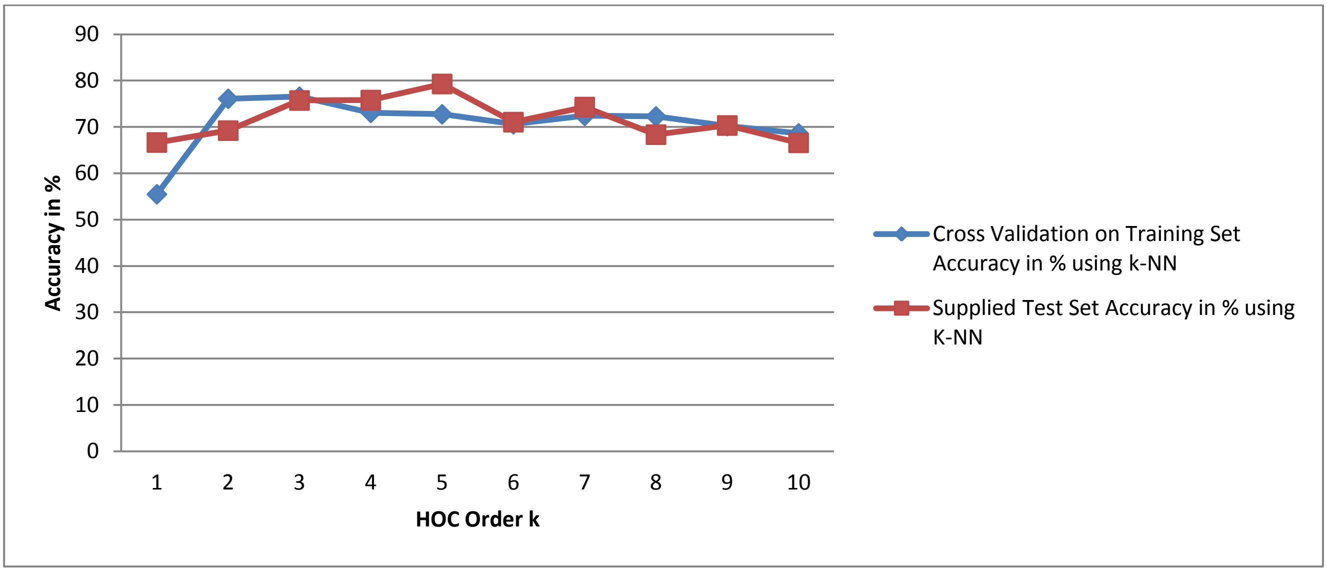

Figure 5.11: Classifier Accuracy on 5 Subjects with Session 1, Session 2 and Session 3 using k-NN

Below Figure 5.12 compares the accuracy of SVM & k-NN Classifiers for 5 Subjects with Session 1, Session 2 and Session 3 using enterface06 database.

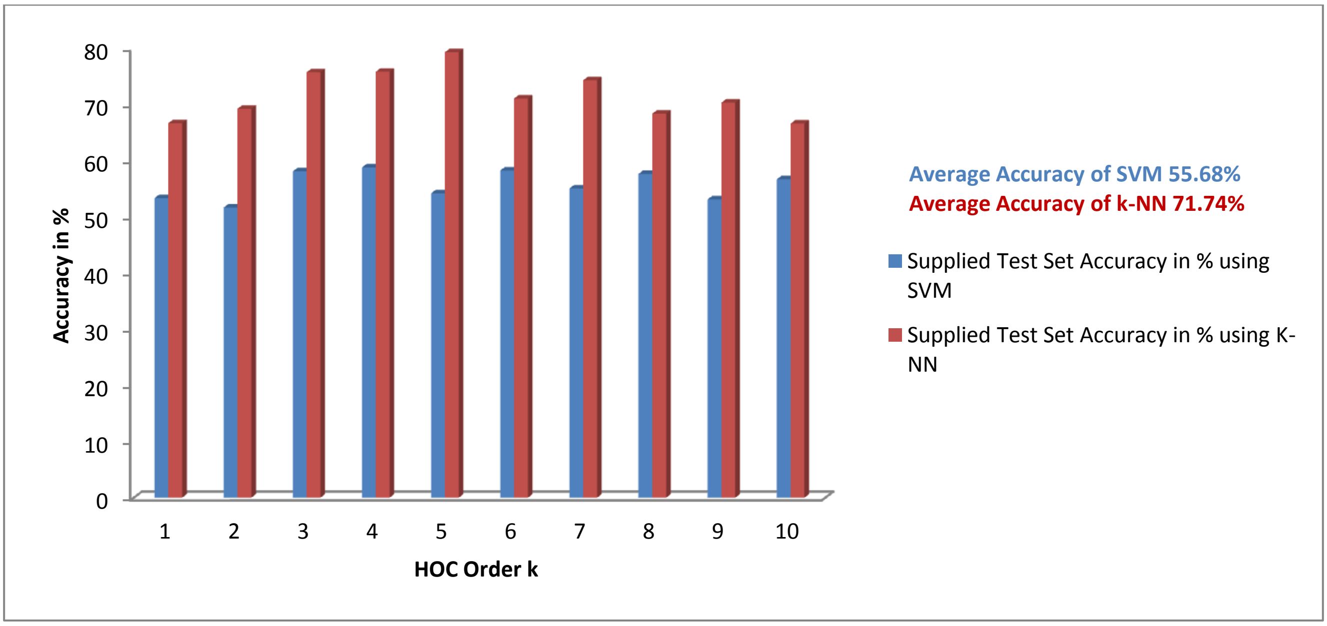

Figure 5.12: Comparison of Accuracy of SVM & k-NN on 5 Subjects with Session 1, Session 2 and Session 3

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

In this dissertation, we have investigated Higher Order Crossings (HOCs) as features for extraction and classifying emotions into affective states from EEG signals. EEG signals were collected from eight subjects using seven electrodes and two pattern recognition methods have been used: k-NN and SVM to classify emotions into two emotional states namely Calm i.e. HVLA (High Valence Low Arousal) and Negatively Exciting (Neg) i.e. LVHA (Low Valence High Arousal), giving best accuracy of 75.76% using k-NN and 64.24 % using SVM. Our recognition rate of 75.76% using k-NN classifier is higher than achieved previously (69.66%) by [43]. Thus we have shown that with lesser number of channels (electrodes), recognition rates have attained a level that is feasible for emotion recognition. Using these significant number of channels, our recognition rate is much higher than those attained previously (33.98%) by [52] .Our recognition rate of 71.76% using k-NN is greater than those achieved previously (65%) by [25] on the same enterface 06 database, for same number of subjects. We have also shown that alpha and beta band features are suitable for emotion recognition tasks as mentioned by [51] . The present procedure for off-line acquisition of physiological signals is very similar to those attained in BCI community so that the conclusions drawn from this study may have some impact in this direction. An emotion evoking task can then be referred to as a mental task that the user tries to perform in order to interact with the environment. This can be useful for severely disabled people who cannot directly express their emotions. For the future studies, larger data sets will be utilized to explore the effect of the number of samples per subject, the number of EEG channels and the number of emotion classes based on the recognition rate.

References

[1] R. Horlings, “Emotion recognition using brain activity,” *Delft University of technology, Man-Machine Interaction Group,* 27 March 2008.

[2] Y.P. Lin, C.H. Wang, T.P. Jung, T.L. Wu, S.K. Jeng, J.R. Duann, and J.H. Chen, “EEG-Based Emotion Recognition in Music Listening,” *IEEE Transactions on Biomedical Engineering IEEE Trans. Biomed. Eng.*, vol. 57, no. 7, pp. 1798–1806, 2010.

[3] A.Choppin, “EEG-based human interface for disabled individuals: Emotion expression with neural networks,” *Master's thesis, Tokyo Institute of Technology,* 2000.

[4] E. Niedermeyer, and F.H. Lopes da Silva, “Electroencephalography: Basic Principles, Clinical Applications, and Related Fields,” *Lippincot Williams & Wilkins,* 2005.

[5] M. Othman, A. Wahab, and R. Khosrowabadi, “MFCC for robust emotion detection using EEG,” in *In proceedings of the 2009 IEEE 9th Malaysia International Conference on Communications,* December 2009.

[6] R.J. Wolpaw, N. Birbaumer, D. J. McFarland, G. Pfurtscheller, and T. M. Vaughan, “ Brain-computer interfaces for communication and control,” *Clinical Neurophysiology,* vol. 113, no. 6, pp. 767-791, March 2002.

[7] J. Wang, , N. Yan, H. Liu, M. Liu, and C. Tai, “ Brain-computer interfaces based on attention and complex mental tasks,” *In Proceedings of International Conference on Digital Human Modeling,* pp. 467-473, Springer Berlin Heidelberg, 2007.

[8] R.Plutchik, “The Emotions: Facts, Theories and a New Model,” *Random House, New York,* 1962.

[9] P. Ekman, W. V. Friesen, M. O'Sullivan, A. Chan, I. D.-Tarlatzis, K. Heider, and R. Krause , “Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion,” *Journal of Personality and Social Psychology,* vol. 53, no. 4, pp. 712-717, October 1987.

[10] J.A.Russell, “A Circumflex Model of Affect,” *Journal of Personality and Social Psychology,* vol. 39, pp. 1161-1178, 1980.

[11] M. M. Bradley, and P. J. Lang, “Measuring emotions: The self assement manikin and the

semantic differential," *Journal of behavior therapy and experimental psychiarty,* vol. 25, no.1, pp. 49-59, March 1994.

[12] P. J.Varghese, " Analysis of EEG signal for EEG-based brain computer interface," *Master's thesis, School of Innovation, Design and Technology,* 2009.

[13] D.O.Bos, "EEG-based emotion recognition," *The Influence of Visual and Auditory Stimuli,* pp. 1-17, 2006.

[14] R. Cowie, E. D. Cowie, N. Tsapatsoulis, G. Votsis, S. Kollias, W. Fellenz, and J. G. Taylor, "Emotion recognition in human computer interaction," *IEEE Signal Processing Magazine,* vol. 18, no.1,pp. 32-80, 2001.

[15] A.-B. R. Suleiman, and T. A. H. Fatehi, "Feature extraction techniques of EEG signal for BCI Applications," *Faculty of Computer and Information Engineering Department College of Electronics Engineering, University of Mosul, Iraq,* 2011.

[16] Human Brain available at http://www.livescience.com/29365-human-brain.html . [Online].

[17] "Brain waves available at http://www.brainworksneurotherapy.com/what-are-brainwaves".

[18] Takahashi, Kazuhiko, "Remarks on emotion recognition from bio-potential signals," *2nd International Conference on Autonomous Robots and Agents,* pp. 186-191, 2005.

[19] Kim, Kyung Hwan, S. W. Bang, and S. R. Kim, "Emotion recognition system using short term monitoring of physiological signals," *Springer Medical and Biological Engineering and Computing,* vol. 42, no.3, pp. 419-427, 2004.

[20] Mandeep Singh, Mooninder Singh, and Surabhi Gangwar, "Emotion Detection Using Electroencephalography (EEG):A Review," *International Journal of Information Technology & Knowledge Management,* vol. 7, no. 1, pp. 1-5, December 2013.

[21] Jurcak, Valer, Daisuke Tsuzuki, and Ippeita Dan, "10.20, 10/10 and 10/5 systems revisited, their validity as relative head surface based positioning systems," *Neuro image,* vol. 34, no. 4, pp. 1600-1611, 2007.

[22] Picard, Rosalind W., Elias Vyzas and Jennifer Healey, "Toward machine emotional intelligence: analysis of affective physiological state," *IEEE Transaction on pattern analysis*

and machine intelligence, vol. 23, no. 10, pp. 1175-1191, October 2001.

[23] Babiloni, Fabio, Luigi Bianchi, Francesco Semeraro, J. del R Millan, Josep Mouriño, Angela Cattini, Serenella Salinari, Maria Grazia Marciani, and Febo Cincotti, "Mahalanobis distance-based classifiers are able to recognize EEG patterns by using few EEG electrodes," *Proceedings of the 23rd Annual International Conference of the IEEE,* vol. 1, pp. 651-654, 2001.

[24] K.Takahashi, "Remarks on emotion recognition from bio-potential signals," *2nd International Conference on Autonomous Robots and Agents,* pp. 186-191, 2004.

[25] Khalili, Z., and M. H. Moradi, "Emotion detection using brain and peripheral signals," *IEEE Cairo International Biomedical Engineering Conference,* pp. 1-4, 2008.

[26] Savran, Arman, Koray Ciftci, Guillaume Chanel, Javier Mota, Luong Hong Viet, Blent Sankur, Lale Akarun, Alice Caplier, and Michele Rombaut, *"Emotion detection in the loop from brain signals and facial images",* 2006.

[27] R.Horlings, ""Emotion recognition using brain activity"," *Man-Machine Interaction Group TU Delft,* March 2008.

[28] . Frantzidis, Christos A., Chrysa D. Lithari, Ana B. Vivas, Christos L. Papadelis, Costas Pappas, and Panagiotis D. Bamidis, "Towards emotion aware computing: a study of arousal modulation with multichannel event-related potentials, delta oscillatory activity and skin conductivity responses," *In Proceedings of 8th IEEE International Conference on Bio Informatics and Bio Engineering,* pp. 1-6, 2008.

[29] Murugappan, Muthusamy, Ramachandran Nagarajan, and Sazali Yaacob, "Comparison of Different Wavelet Features from EEG Signals for Classifying Human Emotions," *IEEE Symposium on Industrial Electronics and Applications,* vol. 2, pp. 836-841, 2009.

[30] Frantzidis, Christos A., Charalampos Bratsas, Christos L. Papadelis, Evdokimos Konstantinidis, Costas Pappas, and Panagiotis D. Bamidis, "Toward emotion aware computing: An integrated approach using multichannel neurophysiological recordings and affective visual stimuli," *IEEE Transactions on Information Technology in Biomedicine,* vol. 14, no. 3, pp. 589-597, 2010.

[31] Khosrowabadi, Reza, Hiok Chai Quek, Abdul Wahab, and Kai Keng Ang, "EEG-based emotion recognition using self- organizing map for boundary detection," *20th International Conference on Pattern Recognition,* pp. 4242-4245, August 2010.

[32] Chai, Tong Yuen, San San Woo, Mohamed Rizon, and Ching Seong Tan, "Classification of Human Emotions from EEG Signals using Statistical Features and Neural Network," *International Journal of Integrated Engineering,* vol. 1, no. 3, pp. 1-6, 2010.

[33] Petrantonakis, Panagiotis C., and Leontios J. Hadjileontiadis, "Emotion recognition from EEG using higher order crossings," *IEEE Transactions on information Technology in Biomedicine,* vol. 14, no. 2, pp. 186-197, 2010.

[34] Xu, Haiyan, and Konstantinos N. Plataniotis, "Affect recognition using EEG signal," *IEEE 14th International Workshop on Multimedia Signal Processing,* pp. 299-304, 2012.

[35] Mandeep Singh, Mr Mooninder Singh, and Nikhil Singhal, "Emotion Recognition along valence Axis Using naive bayes Classifier," *International Journal of Information Technology & Knowledge Management,* vol. 7, no. 1, pp. 51-55, December 2013 .

[36] Mandeep Singh, Mooninder Singh, and Nikhil Singhal, "ANN Based Emotion Recognition along Valence Axis Using EEG," *International Journal of Information Technology & Knowledge Management,* vol. 7, no. 1, pp. 56-60, December 2013.

[37] Mandeep Singh, Mooninder Singh, and Surabhi Gangwar, "Feature Extraction from EEG for Emotion Classification," *International Journal of Information Technology & Knowledge Management,* vol. 7, no. 1, pp. 6-10, December 2013.

[38] Mandeep Singh, Mooninder Singh, "Arousal Detection Using EEG Signal," *International Journal of Information Technology & Knowledge Management,* vol. 7, pp. 11-15, December 2013.

[39] Dan-Glauser, Elise S., and Klaus R. Scherer, "The Geneva affective picture database (GAPED): a new 730-picture database focusing on valence and normative significance," *Behavior Research Methods,* vol. 43, no.2, pp. 468-477, 2011.

[40] Jatupaiboon, Noppadon, Setha Pan-ngum, and Pasin Israsena, "Emotion Classification using Minimal EEG Channels and Frequency Bands," *International Joint Conference on Computer*

Science and Software Engineering, pp. 21-24, May 2013.

[41] Mandeep Singh, Mooninder Singh, and Ankita Sandel, "Emotion Classification along Valence Axis using ERP Signals," *International Journal of Information Technology & Knowledge Management*, vol. 7, pp. 143-152, June 2014.

[42] Mandeep Singh, Mooninder Singh, and Ankita Sandel, "Emotion Classification along Valence Axis using averaged ERP Signals," *International Journal of Information Technology & Knowledge Management*, vol. 7, pp. 153-161, June 2014.

[43] Zheng, Wei-Long, Jia-Yi Zhu, Yong Peng, and Bao-Liang Lu, "EEG-based emotion classification using deep belief networks," *IEEE International Conference on Multimedia and Expo (ICME)*, pp. 1-6, 2014.

[44] Lang, Peter J., Margaret M. Bradley, and Bruce N. Cuthbert, "International affective picture system (IAPS): Technical manual and affective ratings," *NIMH Center for the Study of Emotion and Attention*, pp. 39-58, 1999.

[45] Mandeep Singh, Mooninder Singh, Money Goyal, "Emotion classification using EEG Entropy," *International Journal of Information Technology & Knowledge Management*, vol. 8, June 2015.

[46] Mandeep Singh, Mooninder Singh, Money Goyal, "Comparison of ERP & Entropy based Emotion Classification using EEG signals," *International Journal of Information Technology & Knowledge Management*, vol. 8, no. 2, pp. 150-158, June 2015.

[47] Acqknowledge 4 software guide available "http://www.biopac.com/Manuals/acqknowledge%204%20software%20guide.pdf"

[48] K. C. Arman Savran, "Emotion detection in the loop from brain signals and facial images," *In: Proceedings of the eNTERFACE 2006 Workshop*, 2006.

[49] "Enterfacewebsite 06, http://www.enterface.net/," [Online].

[50] C. P. Niemic, "Studies of emotion: A theoretical and empirical review of psychophysiological studies of emotion," *J. Undergraduate Res.*, vol. 1, pp. 15-18, 2002.

[51] Rowland, N., M. J. Meile, and S. Nicolaidis, "EEG alpha activity reflects attentional demands,

and beta activity reflects emotional and cognitive processes," *Science*, vol. 228, pp. 750-752, June1985.

[52] Petrantonakis, Panagiotis C., and Leontios J. Hadjileontiadis, "Emotion Recognition from EEG Using Higher Order Crossings," *IEEE Trans. Information Technology in Biomedicine,* vol. 14, no. 2, pp. 186-197, March 2010. .

[53] Kedem, Benjamin, and Sidney Yakowitz, "Time Series Analysis by Higher Order Crossings, Piscataway," *IEEE Press*,New York, 1994.

[54] Petrantonakis, Panagiotis C., and Leontios J. Hadjileontiadis, "EEG-Based Emotion Recognition Using Hybrid Filtering and Higher Order Crossings," *Proc. Int'l Conf. Affective Computing and Intelligent Interaction,* pp. 1-6, September 2010.

[55] Holmes, Geoffrey, Andrew Donkin, and Ian H. Witten, "WEKA: A Machine Learning Workbench," *Inte Proceedings of the 1994 Second Australian and New Zealand Conference on. IEEE,* pp. 357-361, 1994.

[56] Hall, Mark, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, and Ian H. Witten, "The WEKA data mining software: an update," *ACM SIGKDD explorations newsletter* , vol. 11, no, 1,, pp. 10-18, 2009.

[57] J. Platt, "Sequential minimal optimization: A fast algorithm for training support vector machines," pp. 1-21, April 1998.

[58] T. Joachims, "Text categorization with support vector machines: Learning with many relevant features," *European conference on machine learning,* pp. 137-142, April 1998.

[59] Hall, Mark, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, and Ian H. Witten, "Performance of k-NN classifier for emotion detection using EEG signals," *Communications and Signal Processing (ICCSP), 2015 International Conference on. IEEE,* vol. 11, no. 1, pp. 10-18, 2009.

[60] K. M. Dr. R J Ramteke, "Automatic Medical Image Classification and Abnormality Detection Using k- Nearest Neighbor," *International Journal of Advanced Computer Research,* vol. 2, no. 4, pp. 190-196, December 2012.

[61] R. Kohavi, "A study of cross-validation and bootstrap for accuracy estimation and model

selection," *Proceedings of the Fourteenth International Joint Conference on Artificial Intelligence,* vol. 14, no.2, pp. 1137-1143, 1995.

Sonakshi_thesis

ORIGINALITY REPORT

20%	5%	10%	11%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Thapar University, Patiala Student Paper	8%
2	Petrantonakis, Panagiotis C., and Leontios J. Hadjileontiadis. "Emotion Recognition from Brain Signals Using Hybrid Adaptive Filtering and Higher Order Crossings Analysis", IEEE Transactions on Affective Computing, 2010. Publication	2%
3	Xu, Haiyan, and Konstantinos N. (Kostas) Plataniotis. "Affect recognition using EEG signal", 2012 IEEE 14th International Workshop on Multimedia Signal Processing (MMSP), 2012. Publication	2%
4	Submitted to The Hong Kong Polytechnic University Student Paper	1%
5	www.csjournals.com Internet Source	1%
6	Petrantonakis, P.C., and L.J. Hadjileontiadis. "Emotion Recognition From EEG Using Higher Order Crossings", IEEE Transactions	1%