AROUSAL DETECTION BY EEG ENTROPY AND ERP

A Dissertation submitted in fulfillment of the requirements for the Degree

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MASTER OF ENGINEERING

in

Electronics Instrumentation & Control Engineering

Submitted by

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DECLARATION

I hereby certify that the work which is presented in dissertation entitled, "**Arousal Detection by EEG Entropy and ERP**" in partial fulfillment 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. Moon Inder 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.

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LIST OF ABBREVIATIONS

ALS- Amyotrophic Lateral Sclerosis

ANN-Artificial Neural Network

CNS- Central Nervous System

EEG- Electroencephalogram

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

IAPS- International Affective Picture System

KNN- K-Nearest Neighbor

LDA - Linear Discriminate Analysis

LIBSVM - Library For Support Vector Machines

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

STFT- Short Time Fourier Transform

OUTLINE OF THE DISSERTATION

This dissertation consists of 6 chapters which have been introduced as follows to get an overview of the study carried out. It is initiated by introducing the overview of our research on emotions which is followed by necessity of developing an affective (BCI) Brain Computer Interface module, interpretation of the EEG signals in time- frequency domain in **Chapter 1.** The chapter 1 is followed by Human brain function and the best method suitable for measuring brain activity is explained in **Chapter 2**. Review of previous research work done by various researchers for the quantification of emotions and their contributions in this interesting field. Comparisons have also been made for the different methodologies used in various studies. In the end, the previous works discussed have also been summarized in **Chapter 3. Chapter 4** describes the methodology used in our study for acquisition and Feature extraction for classification of emotions. In **Chapter 5** describes the accuracy results for five subjects in the form of tables and bar graphs. At last, the **Chapter 6** concludes the research and outline guidelines for future work. The significance of the study has been mentioned and the improvements that can be made have also been discussed.

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 behavior 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 F3, F4 and FZ from five subjects for classification of emotions into two classes namely HVHA and LVHA. The images provided by International Affective Picture System (IAPS) have been used for evoking emotions. The data has been acquired by placing a cap on the head of a subject as per 10-20 International system. The obtained EEG signal has been filtered in offline mode 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. The ERP potentials such as P100, N100 and the two latencies corresponding to these bio potentials have been extracted for every class of emotion from filtered EEG signals. The EEG signal is decomposed into five different frequency bands namely delta (0-4 Hz), theta (4–8 Hz), alpha (8–16 Hz), beta (16–32 Hz) and gamma (32- 64Hz) by using filtering technique. The entropy attribute from these five frequency bands has been extracted. The training and testing has been performed on the eleven combinations extracted from four attributes of ERP. The six combinations extracted from Entropy attribute is also used for classification. The classification has been performed using LIBSVM classifier with 3 fold cross validation and RBF kernel to classify emotions into two classes.

CHAPTER 1

INTRODUCTION

Overview

Emotions play a significant task in how we interact with our outside world. One of the commonly accepted definitions of emotion is "An intense feeling driving from one's mood, circumstances and relationship with others" [1]. It is a kind of non verbal communication that helps in making the communication smooth. It not only influences our actions but as well affect the way we communicate with other people. This means it is a necessary aspect in interaction between people. For example, a person driving on a road in bad mood is not only dangerous to himself but also to other commuters on the road. Thus it is not only necessary to study emotion but as well becomes necessary to design a methodology to bring the subjects from high arousal state to a calm state of mind. So this requires a development of an affective emotion classifier. Without the emotion processing even computers and robot cannot communicate with human being in natural way [2]. The emotions can be evoked in a laboratory by using various methods such as audio and/or visual stimuli or by asking the subject to think about a particular situation. The emotions can be studied by deriving different attributes from the subject's speech, facial expressions, and body gestures [3] but these reactions can be faked by the subject under observation. Moreover, these modalities cannot be effectively used by people who are rigorously afflicted from stroke, paralysis, Amyotrophic lateral sclerosis (ALS) [4] and other brain related disorders because they lose their ability to speak or to communicate with environment. In other words, the emotion recognition becomes necessary for the benefit of persons in locked conditions. So it becomes necessary to study the changes in physiological parameters with emotional changes. In this dissertation main focus is given towards processing of electro-encephalogram (EEG) signals for classification of emotions. EEG is a method of measuring voltage fluctuations within the neurons of the brain resulting from ionic current [5]. It is a method of extracting data with benefits like simple, fast, noninvasive and inexpensive method and extensively used in biomedical study and clinical diagnosis. For these reasons emotion recognition using EEG signals is a well known and preferred method [6]. In our study EEG signal is acquired at sampling rate of 500 samples per second from emotion evoking images provided by International Affective Picture System (IAPS) [7]. This EEG data has been processed to obtain noise free signal with in a frequency range of 0.5 to 40Hz. Different types of attributes has been extracted and thus combinations has been tested using an appropriate machine learning algorithm to classify the emotions into two classes- Low Arousal (Negative) and High Arousal (Positive).

Emotions

Emotions play a key role in our daily interaction with outside world. It is a versatile phenomenon which can predict the mood and behavior of person in that mood. Emotions are described as feelings of human being that represent the personality of any individual which include different experiences such as love, hate, trust, anger, fear. One of the accepted definitions of emotion as: An emotion is defined as particular activity of brain and a reflection of human expressions for specific person for the particular function in distinct environmental conditions [8].

1.2.1 Basic Emotions

Different researches give different model on emotions. The first model was given by Darwin which further processed by Plutchik and Ekman. Plutchik considered that there are eight basic emotions namely sadness, disgust, joy, surprise, anger, fear, joy acceptance, and curiosity [9] whereas Ekman considered that all emotions are made up of six basic feelings such as happiness, anger, fear, disgust, sadness and surprise [10]. Some basic emotions namely happy, sad, surprised, angry, excited, frustrated, calm, shocked and naughty are some of the emotions we feel in our daily life. Figure 1.1 shows the basic emotions of our daily life.

Figure 1.1: Basic Emotions

Brain Computer Interface

Brain Computer Interface (BCI) is associated with study of interaction between the computers and human being. Mostly computers unable to understand the needs of human being to respond automatically so it is not possible to correctly identify the all emotional states of human to take the appropriate actions. Human computer interface implementations can help us in entertainment, electronics, in military and civil and even in medical profession to understand the human emotions. For example a person suffering from serious disease may be not able to communicate with environment to process information. This requires the utilization to study brain and physiological signal and using them together in human computer implementation to understand the emotions of human being. It can helps in reducing the communication hindrance with the environment. Brain Computer Interface (BCI) system consists of various components such as signal acquisition, signal processing, feature extraction\selection and classification and a feedback presentation system. Figure 1.2 shows an affective brain computer interface module.

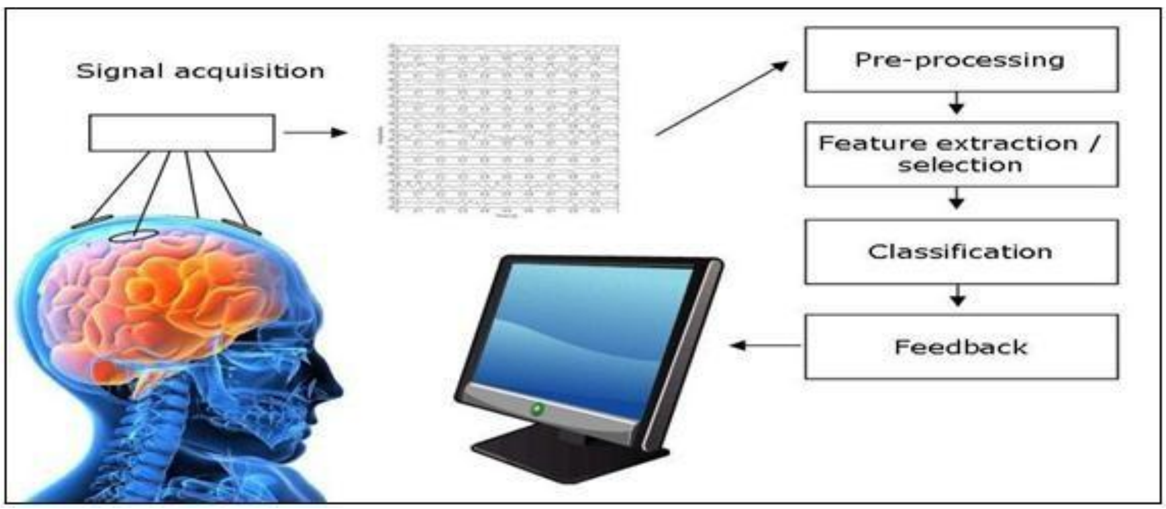


Figure 1.2: Brain Computer Interface [11]

Human ideas modulate the electrical brain signals which are recorded and detected by the signal acquisition block and then filtered by the signal preprocessing block. The preprocessed signal is used for extracting the features which are used to classify emotions. During the processing of these actions, some feedback may be give back to the users to apply a corrective action in case necessary [12]. Commonly acquired physiological signals for emotion recognition are Blood Pressure, Galvanic Skin Response (GSR), and Heart Rate and EEG signals etc. Generally Central Nervous System (CNS) and the Peripheral Nervous System (PNS) result into origin of physiological signals. Among other physiological signals, EEG signal gained remarkable interest because an emotion is a psychological process which is associated with brain activity [13-15].

Quantification of Emotions

Russell, J.A. (1980) developed a circumflex model of affect in which emotions were described in a two dimensional space. According to his approach feelings like angry, fear, happiness, joy, depressed, displeasure are interconnected means not independent. The emotional states in which pleased was along the x-axis and the level of activation represented y-axis. The emotion describing words were so placed that the like meaning words were closer while the opposites lied diagonally [16]. Later this model was modified by Lang et al where the two dimensions were represented by valence and arousal [17]. Figure 1.3 shows the circumflex model of affect.

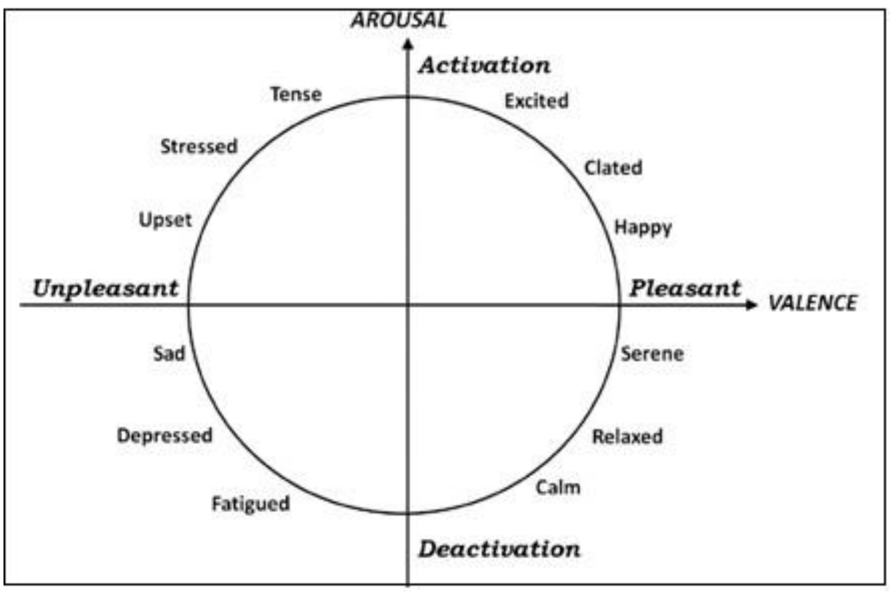


Figure 1.3: A circumflex model [18]

Dimensional View of Emotions

Emotional model given by researcher considered multiple dimensions in which every emotion occurs on multidimensional scale, the first dimension was valence in which positive valence on one and negative valence on other side. The second dimension contains the arousal in which positive arousal on one and negative arousal on other side. The third dimension contains the dominance which was rarely used, and always not the same when used. Sometimes it was motor activation on third dimension. Using Self-Assessment Manikin Method (SAM), valence and arousal can be defined in which SAM rating was ranging from 1 to 9. The dimensional view of emotions represents valence along x axis and arousal along y axis. The maximum value of valence represents the positive condition of emotions means person is happy and lowest value of valence represent the negative condition of emotions means person is sad. In the same way, the maximum value of arousal represents the level of excitation means person on HVHA state and a person in HVLA means a person is in calm state.

Classes of Emotions

Emotions can be recognized along Valence and Arousal axis resulting into four quadrants. Valence along x axis is divided into two classes' namely Positive Valence means high and Negative Valence means low keeping the arousal state of emotion constant. Similarly arousal along y axis is divided into two classes' namely Positive Arousal means high and Negative Arousal means low keeping the valence state of emotion constant It leads to four emotional states namely High Valence High Arousal (HVHA), Low Valence High Arousal (LVHA), High Valence Low Arousal (HVLA) and Low Valence Low Arousal (LVLA) states depend upon the arousal and valence state of emotions. Figure 1.4 shows the four emotional states.

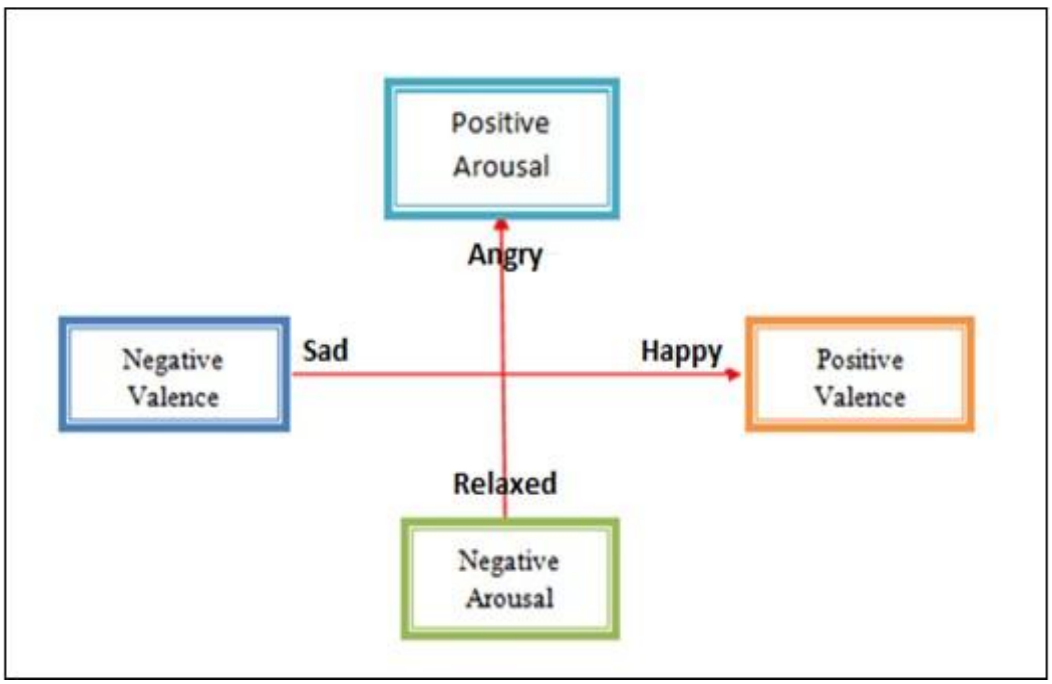


Figure 1.4: Dimension of emotions

CHAPTER 2

HUMAN BRAIN AND EEG

Human Brain

Brain is the most complex organ of central nervous system. Human brain is protected by skull which is located in the head of human brain. It is composed of blood vessels, glial cells and neurons which are linked by trillion of connections. An average weighs of adult human brain is about 1.3–1.4 kg with mushroom shaped structure [19]. It is centre control of all actions such as sleep, hunger, internal temperature, even breathing and every other crucial activity needed to survive for human being. Human brain is divided into three parts namely cerebrum, cerebellum and brainstem. Cerebrum is the largest part of the human brain, which is divided into two hemispheres: underneath lies the brainstem, and at the back lies the cerebellum. Cerebrum is associated with major brain function such as thoughts, vision, touch, sensing temperature, emotions and learning. The middle portion of human brain is called brainstem which is responsible for regulation of hunger, respiratory and cardiac function of human body. It consists of the medulla oblongata, pons and midbrain. Cerebellum is the smallest part of human brain which receives information from the spinal cord, sensory systems, and other parts of the brain then results in regulation of motor movements [20].

Cerebral cortex is the outermost layer of the cerebrum, which consists of four lobes:

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

Brain Lobes

Frontal Lobe- It is located in front of parietal lobe and of temporal lobe of human brain. It is one of the largest sections of brain and is associated with reasoning, high level cognition, motor skills and expressive language. The space between tissues called central sulcus which separates the frontal lobe from the parietal lobe. Frontal lobe is the area responsible for receiving information from various lobes of brain and makes use of this information to carry out body movements. Any damage to frontal lobe can results in mood changes of human being [21].

Parietal Lobe- Parietal lobe is located behind the frontal lobe and central sulcus and above the occipital lobe of human brain. It is middle part of human brain. This lobe is separated from occipital lobe by parietal-occipital sulcus and the central sulcus separates the parietal lobe from the frontal lobe [22]. It carries out very specific function related to process sensory information such as touch, pressure, pain from various parts of body within seconds. If parietal lobe damaged, human being cannot be able to feel the sense of touch.

Occipital Lobe- Occipital lobe is located in the back side of cortex. It is the smallest lobe of all paired lobes and responsible for interpreting visual stimuli and able to correctly understand what our eyes are sending to lobe of human brain. Damage to occipital lobe can cause visual problems such as difficulty in color identification and object recognition [23].

Temporal Lobe- Temporal lobe is located at inferior to parietal and frontal lobe and anterior to the occipital lobe of human brain. It means is located at sides of human brain. Temporal lobe is accountable for processing auditory information such as sound and speech received from the ears. Any damage to temporal lobe can lead to problem with visual perception, memory, and language skills and person will unable to listen [24]. All the lobes of brain are shown in Figure 2.1.

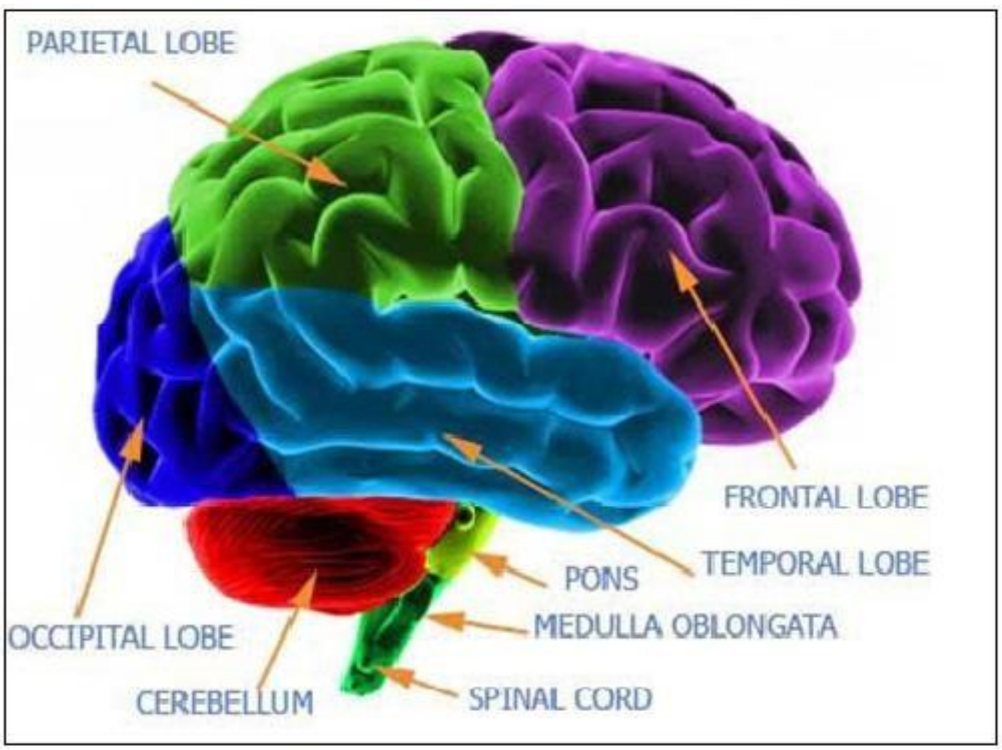


Figure 2.1: Brain Lobes [25]

2.3 Brain Waves

Our thoughts and emotions are the root of communication between neurons. Because of communication between neurons, synchronized electrical pulses are produced resulting into brain waves. By placing sensors on scalp brain waves are detected. Brain waves changed according to our activities in our daily life means what we are feeling and doing [26]. These are measured in Hz (cycles per second) and divided into five types namely

1. Delta wave
2. Theta wave
3. Alpha wave
4. Beta wave
5. Gamma wave

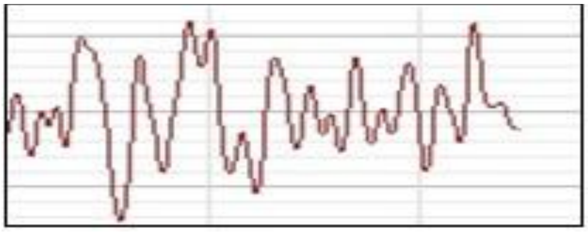
Delta wave- It has a frequency range between 0 to 4 Hz. These are the slowest but deep penetrating like a drum beat brainwave. Delta wave produced with dreamless sleep and in condition of deepest meditation. In the state of delta wave, healing and regeneration are stimulated so deep restorative sleep is necessary to healing process.

Theta wave- It has a frequency range between 4 to 8 Hz and it is classified as "slowest "wave of human brain. These waves mostly occur during sleeping condition but can also in deep meditation. It acts as access to learning and memory. A person is who sleep in morning is more prone to production of theta waves. With the production of theta waves, more ideas will be in flowing in human brain.

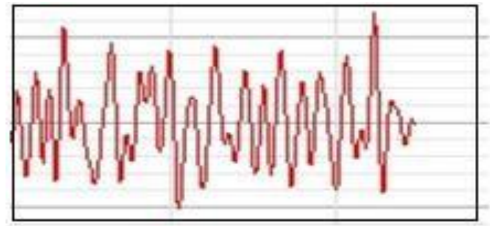
Alpha wave- Alpha waves mainly originate from occipital lobe of brain with frequency range of 8 to 12 Hz. Open eyes, sleep and drowsiness will reduce production of alpha wave. A person is said to be in alpha state if suddenly takes break from work to have relaxation. Alpha waves increase overall mental coordination, mind/body Integration, calmness and learning.

Beta waves- Beta wave is classified as "fast" activity with frequency range of 12 to 30 Hz. The amplitude of beta wave is low. A person, who is continuously engaged in doing work beta wave, will emit and when we are alert beta waves will emit. For example Brain will replicate beta waves in case of person who is doing debating or teacher who is teaching.

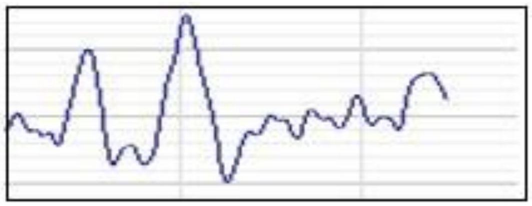
Gamma wave- Gamma waves are related to spontaneous processing of information from different lobes of brain with frequency more than 30 Hz. It is classified as "fastest" wave like a flute. This wave does not occur during deep sleep stimulated by anesthesia, but come back with transition occurring in wakeful state [27]. Various brain waves are shown in Figure 2.2.



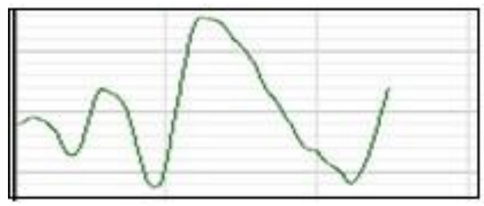
Alpha wave



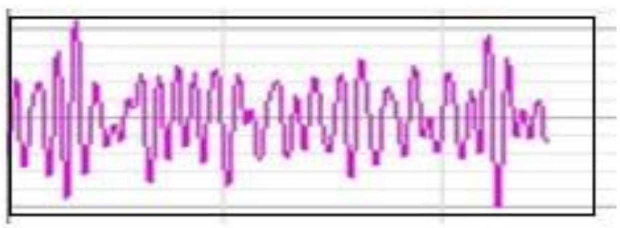
Beta wave



Theta wave



Delta wave



Gamma wave

Figure 2.2: Brain waves

Brain Activity Measurement

Human brain is the part of human body which regulates all the activities of human. It is composed of neurons results into production of brain waves. These waves can be measured using different techniques such as Functional Magnetic Resonance Imaging (FMRI), Positron Emission Tomography (PET) and Electroencephalography (EEG).

Functional Magnetic Resonance Imaging

Functional Magnetic Resonance Imaging measure the brain activity by detecting the change in flow of oxygenated blood. Brain consumes more oxygen when it is more active so to meet this demand oxygenated blood flows to the active area of brain. This technique can be used to produce activation maps indicating which part was involved in particular psychological process. The advantage of using FMRI is good spatial resolution and non invasive method but low temporal resolution and very expensive [28]. Figure 2.3 shows the FMRI scan system for measuring brain activity.

Figure 2.3: FMRI scanning system [29]

Positron Emission Tomography

It is a technique which produces three dimensional images of brain activities in human body. To measure the blood flow radioactive isotope is injected into blood. This radioactive isotope emit positron and taken with the flow of blood because blood flow in the brain is totally linked with brain activity. It is able to measure brain activity with high spatial resolution but time consuming process and requires exposure of radiations for brain activity. Figure 2.4 shows the PET scan system for measuring brain activity.

Figure 2.4: PET emission scanning system [30]

EEG

Electroencephalogram (EEG) is a method of measuring electrical activity from scalp of human brain. This electrical activity is a result of firing of millions of neurons with in brain and final electrical signal is taken by placing electrodes on scalp. EEG cap is used for recording of electrical signal when electrodes are placed on person's scalp through cap. Electrodes are filled with conductive gel to make contact between electrodes and scalp. One of the applications of EEG is in identification of emotions and diagnosing epilepsy. As emotions cannot be identified directly from signal, since it require the preprocessing and feature extraction from signal to analyze the emotional state. Various researches are done by researchers for finding the relationship between the emotions and EEG signals [31]. Using the combination of both EEG signal and peripheral signals such as Blood Pressure, Galvanic Skin Response (GSR), and Heart Rate classification was performed [31-32]. But most researches considered only EEG signals for emotion quantification [33]. As emotions can be predicted from other techniques also such as Positron Emission Tomography, Functional Magnetic Resonance Imaging but these techniques are very slow and depend on alteration in blood composition of human being [34]. So the best method is through EEG as it has simple and portable hardware, direct measurement of electrical activity and high temporal resolution [35]. EEG signal acquired is shown in Figure 2.5.

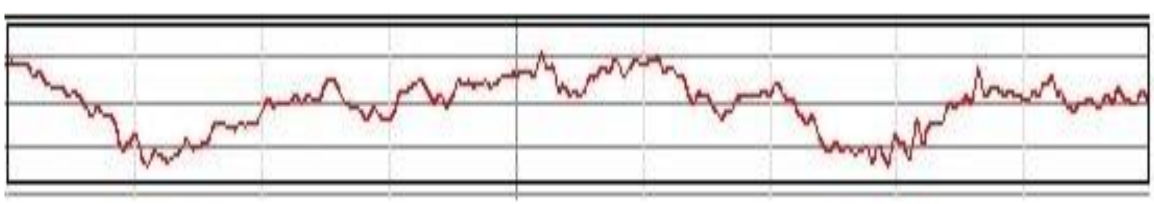


Figure 2.5: EEG signal

2.5 Electrodes

Electrodes play a crucial role in acquisition of EEG signal. All electrodes are placed on the scalp to record the EEG signal. To capture EEG signal emitted from brain, these electrodes make contact with scalp. Since electrodes are made up of Silver/Silver Chloride (Ag/AgCl). The position of electrodes on scalp is according to 10-20 international system which means they are at 10% and 20% of distance between the adjoining electrodes. Every electrode on EEG cap is labeled with an alphabet. The alphabets refers to the lobes of brain hidden under the electrodes namely F refers to Frontal lobe, C refers to Central lobe, P refers to Parietal lobe, T refers to Temporal lobe and O refers to Occipital lobe of brain. Electrodes are designated as even number to right part of brain and odd number to left part of brain under observation. The electrodes can be also being placed directly on scalp or through the use of cap where electrodes are fixed on cap. The available electrodes are of many types such as of tin, gold, or silver with coating of silver chloride is provided. Other methods used for placement of electrodes are mainly 10-10 and 10-5 system. But most preferable is 10-20 system for collecting the EEG signal [36]. The 10-20 International system is shown in Figure 2.6.

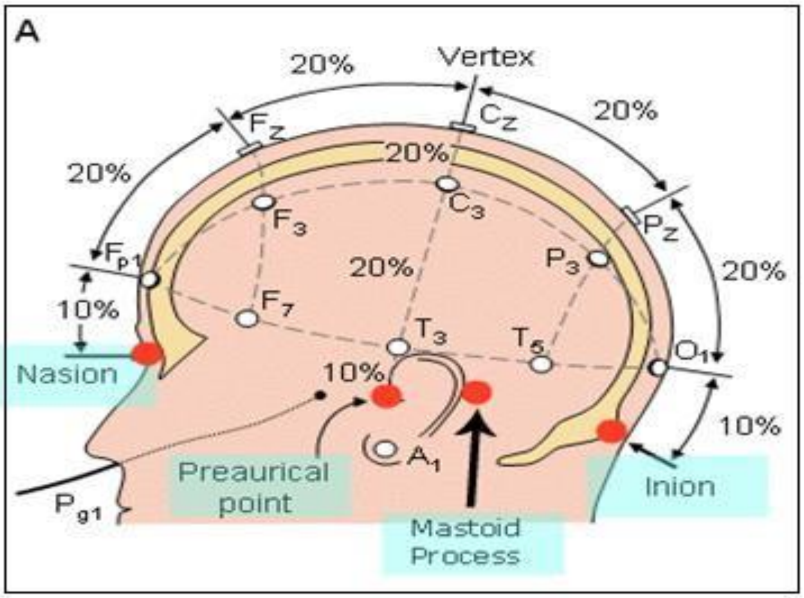


Figure 2.6: 10-20 international System [37]

Here in the study only frontal electrodes are considered for analyzing the EEG signal which is Fz, F3 and F4.

CHAPTER 3

LITERATURE REVIEW

Many researchers followed different terminology for recognition and classification of emotions into various emotional states. Some of the researches done by various author have been discussed in this study and are as follows:

Picard, R.W *et al.* (2001) in their research study worked on eight classes of emotions namely grief, love, hate, romantic love, nature, joy including neutral. The emotions were invoked as per the guidelines laid down by Clynes [8]. To recognize eight emotional states data was gathered from single subject using four sensors namely a triode electromyogram, photoplethysmyograph, skin conductance sensor and Hall Effect respiration sensor. The statistical features such as mean and standard deviation of signals were selected for classification of emotions. The classification of emotional state was performed with Maximum a Posteriori (MAP) classification technique using Fisher analysis. An accuracy of about 80% to 90% was achieved.

Babiloni, F *et al*. (2001) collected EEG signal from eight healthy subjects when different tasks including imagination of movement was performed. The data was collected from four electrodes namely C3, P3, C4 and P4 when placed according to international 10-20 system. The quadratic classifier based on Mahalanobis distance (MD) was used to detect EEG patterns. Classification was performed when reduced set of recording electrodes with covariance and diagonal matrix of EEG data was used by the classifier. An average accuracy of 98% was obtained which made it easy for brain computer interface with reduced set of recording electrodes [38]. Kim, K.H *et al.* (2004) collected physiological database such as electrocardiogram and skin temperature variations from fifty participants. The emotions were classified into four emotional states namely sad, anger, stress, surprise to build a user-independent system for recognizing emotions. The classification was performed by support vector machine as pattern classifier with ratios obtained was 78% and 61.8% in case of three and four distinct emotions respectively [32].

Takahashi, K *et al.* (2004) as well used physiological database for classifying emotions into five states namely joy, anger, sadness, happiness and relax from twelve subjects. The classifier used was support vector machines for classification of emotions over setup of three dry electrodes with recognition rate of 41.7% were achieved [31]. Chanel, G *et al.* (2007) classified human emotions into three classes namely negatively excited, positively excited and calm-neutral states using the combination of EEG signals and other physiological signals such as Galvanic Skin Resistance (GSR), Blood Pressure (BP), and Heart Rate (HR). The data was recorded using 64 channels placed according to the 10-20 system from three participants. Both peripheral and EEG signals were sampled at 1024 Hz. The extracted attributes used for classification of emotions include mean value of physiological signals and short-time Fourier Transform of EEG signals. The classification was performed using Linear Discriminant Analysis and a Support Vector Machine using either EEG or peripheral features. The authors concluded that using EEG to classify valence and arousal in emotions is better than peripheral signals [39].

Frantzidis, C. A *et al* (2008) collected the EEG data from central nervous system and skin conductance response from 13 male and female subjects. The emotions were invoked by using the images from IAPS dataset. The pictures from IAPS are divided into four categories named as HVHA means pleasant and having high arousal in upper right corner, and similarly upper left corner denoting as HVLA means pleasant but in low arousal stimuli. In the same way LVHA in lower right quadrant representing unpleasant in high arousal stimuli and LVLA in lower left quadrant is unpleasant in low arousal state. The EEG signals were collected from three central electrodes namely Fz, Cz and Pz. The attributes such as event related potential (ERP), latency, rise time, amplitude and the skin resistance response duration were extracted for classification of emotions. The classification was performed using artificial neural network that yielded an accuracy of 80% for joy, 100% for fear, 80% for happiness, and 70% for melancholy [40].

Horlings, R *et al* (2008) classified emotions into five classes along arousal and valence axis by using the self collected EEG signals from ten subjects and the EEG data acquired in eNTERFACE 2006 workshop [41]. The emotions were invoked using images from IAPS dataset. The features used were EEG frequency band power, cross-correlation between EEG band powers, peak frequency in alpha band and Hjorth parameters. The classification was done using 3 fold cross validation using a neural network and a naive Bayes classifier. With neural networks, classification rate was slightly lower than support vector machines and classification rate was achieved up to 32% for valance dimension and 37% for arousal dimension [33].

Murugappan, M *et al* (2009) collected EEG data from 20 healthy participants when stimulated by audio-visual stimuli. The emotion was classified into five classes namely disgust, happy, surprise, fear and neutral. The EEG signal was decomposed into five different frequency bands (delta, theta, alpha, beta and gamma) using wavelet transforms. The classification was performed using 5 fold cross validation with K Nearest neighbor (KNN) & Linear discriminate analysis (LDA) classifier. An average accuracy of 79.14% was achieved and a maximum subset emotion rate of 91% on disgust, 88% on happy, 60% surprise, 73.75% fear and 87.5 % on neutral emotions was obtained [42].

Frantzidis, C *et al* (2010) acquired the EEG data from 28 healthy subjects when images from IAPS dataset were used for evoking emotions. The emotions were classified into four emotional states in which valence discrimination was performed first and after that arousal discrimination was performed. The attribute extracted was event related potential for three central electrodes namely Fz, Cz and Pz for classification of emotions. The Classification was done by Mahalanobis distance (MD) and Support Vector Machine (SVM) in various chosen kernel namely liner, polynomial and RBF kernel [43]. The classification accuracy achieved is shown in Table 3.1.

Table 3.1: Classification accuracy achieved using different classifiers

Classifier	HVHA	HVLA	LVHA	LVLA	Total
Mahalanobis distance	85.71%	82.14%	78.57%	71.43%	79.46%
Support Vector Machine	85.71%	85.71%	71.43%	82.14%	81.25%

Khosrowabadi, R *et al* (2010) as well collected EEG data from IAPS dataset for evoking of emotions for twenty six subjects over eight channels. The attributes was extracted using the magnitude squared coherence of the EEG signals for classification of emotions into four states namely calm, happy, sad and fear. The boundaries of the EEG features were then extracted using self organizing map. The classification was performed using 5-fold cross validation with k-NN as classifier with accuracy achieved up to 84.5% [44].

Petrantonakis, P.C *et al.* (2010) collected EEG data from sixteen healthy subjects from three EEG channels, namely Fp1, Fp2 and a bipolar channel of F3 and F4 according to position of international 10–20 system. The emotions were classified into six basic emotions states namely happiness, surprise, anger, fear, disgust, and sadness when novel emotion elicitation method based on the Mirror Neuron System was used to promote emotion stimulation. The extracted features using higher order crossings (HOC) were classified with four different classifiers namely quadratic discriminant analysis (QDA), *k*-nearest neighbor, Mahalanobis distance and support vector machines (SVMs) for recognition of emotions. The EEG data examined from single-channel and from combined-channels results in accuracy of 62.3% using QDA and 83.33% using SVM respectively [45]. Yuen, C.T *et al.* (2010) collected EEG data by audio visual stimuli for evoking emotions from three male and female subjects. The emotions was classified into five types of emotions namely anger, sad, surprise, happy, and neutral from 64 channel biosensor. A total of six statistical features were computed from EEG data. The classification accuracy of 95% was obtained when used back propagation neural network as classifier [46].

Anh, V.H *et al.* (2012) collected EEG data when images from IAPS dataset were used for evoking emotions. Two approaches from Russell's circumplex model were used. The algorithm used was Higuchi Fractal Dimension with Support Vector Machine as classifier. First approach was machine learning in which EEG signals of all the participants were taken under consideration and second approach was the machine learning in which EEG signal of individual participants were taken. Since EEG signal of every subject has different characteristic so results showed that first approach was impossible to apply but second approach of individual subjects under consideration was used and can recognize five states of human emotion average accuracy 70.5% [47].

Xu, H *et al.* (2012) collected EEG recordings from 5 subjects with IAPS images as stimuli from the eNTERFACE06 database were used for simulation purposes. The emotions were classified into three emotional states namely positively excited, neutral and negatively excited from 54 electrodes. The discriminating features were extracted in both time and frequency domains such as statistical, narrow-band, HOC, and wavelet entropy. Through the use of k Nearest Neighbor classifier (kNN), the obtained mean correct classification rates of 90.77% on the three emotion classes when K was equals five [48].

Singh, M. *et al.* (2013) as well used the eNTERFACE 06 EEG database for classifying emotions into two classes. Different attributes such as Power Spectral Density (PSD), Short Time Fourier Transform (STFT) and Event Related Potential (ERP) on the basis of time frequency domain were extracted and the classifiers such as ANN and Naïve Bayes were used for classification of emotions into two classes [49-53]. Jatupaiboon, N. *et al.* (2013) collected EEG signals from eleven subjects by emotions evoking pictures from Geneva Affective Picture Database (GAPED) [54]. EEG was recorded over 14 channels for classifying emotions into two classes. The attributes were extracted by decomposing the data into five specific spectral bands namely Delta (0-4 Hz), Theta (4-8 Hz), Alpha (8-16 Hz), Beta (16-32 Hz) and Gamma (32-64 Hz) by Wavelet Transformation. The attributes such as power spectrum from each band was computed. An accuracy of about 85.41% was obtained when 10 -fold cross validation with support vector machine classifier was used [55].

Singh, M *et al.* (2014) extract the EEG signal from three participants which was acquired by emotion evoking pictures from IAPS. The EEG data was collected from three electrodes namely Cz, F3 and F4 for classifying emotions into two classes along valence axis. The Attribute extracted for emotion classification was event related potential and average of event related potential. The classification was done using support vector machines as classifier [56-57].

Zheng, W.L *et al.* (2014) classified emotions into two states (positive and negative) when EEG data was collected by stimulating the subject with emotional movie clips from three male and female subject using 62-channel electrode cap placed according to the international 10-20 system. In addition to this new technique was incorporated namely hidden markov model (HMM) to accurately capture a more consistent emotional stage. The attributes extracted for emotion classification was differential entropy features. Through the use of KNN (k-Nearest Neighbor), SVM (support vector machine), GELM (Graph regularized Extreme Learning Machine), DBN (Deep Belief Networks) and DBN-HMM classifier, an average accuracies of 69.66%,84.08%, 85.67%, 86.91% and 87.62% was achieved. Results showed that using the DBN and DBN-HMM models accuracy of EEG based emotion classification was improved in comparison to other methods [58]. The comparison of methodologies used by different researchers is shown in Table 3.2.

Table 3.2: Comparison of methodologies used by different researchers in their study

Year	Data collection	Emotions classification	Attributes extracted	Classifier used	Reported performanc
2001	EEG data collection using four sensors namely a triode electromyogram, photoplethysmograph, skin conductance sensor and Hall Effect respiration sensor	Eight classes	Statistical features such as mean and standard deviation of signals	Maximum a Posteriori (MAP) classification technique	Accuracy of 80 to 90% obtained [8].
2004	Collected physiological database such as electrocardiogram and skin temperature variations	Four classes	Statistical features	Support vector machines	Accuracy of 78% and 61.8% for three and four distinct emotions [32].
2007	Combination of EEG signals and other physiological signals such as GSR, BP and HR	Three classes	Mean of Physiological Signal and STFT of EEG signal	Liner Discriminant Analysis and Support vector machine	EEG classification better than peripheral signals [39].
2008	EEG data from central nervous system and skin conductance response	Four classes	event related potential (ERP), latency, rise time, amplitude and the skin resistance response duration	Artificial neural network	An accuracy of 80% for joy, 100% for fear, 80% for happiness, and 70% for melancholy [40].
2008	Self collected EEG signals	Five classes	EEG frequency band power, cross-correlation between EEG band powers, peak frequency in alpha band and Hjorth parameters	Neural network and a naive Bayes classifier	An accuracy of 32% for valance dimension and 37% for arousal dimension [33].

Year	Data collection	Emotions classification	Attributes extracted	Classifier used	Reported performanc
2009	EEG data by audio-visual stimuli	Five classes	By decomposing into five different frequency bands using wavelet transforms	K Nearest neighbor (KNN) & Linear discriminate analysis (LDA) classifier	An accuracy of 79.14% with maximum subset emotion rate of 91% on disgust, 88% on happy, 60% surprise, 73.75% fear and 87.5 % on neutral emotions [42].
2010	EEG data by IAPS data set	Four classes	Event related potential	Mahalanobis distance (MD) and Support Vector Machine (SVM)	An accuracy of 79.46% by Mahalanobis distance and 81.25% by SVM [43].
2010	EEG data by IAPS data set	Four classes	Magnitude squared coherence	K-Nearest neighbor(k-NN)	An accuracy of 84.5% [44].
2010	Collected EEG data based on the Mirror Neuron System	Six classes	Using higher order crossings	Quadratic discriminant analysis (QDA), *k*-nearest neighbor, Mahalanobis distance and support vector machines (SVMs)	An accuracy of 62.3% using QDA and 83.33% using SVM [45].
2010	Collected EEG data by audio visual stimuli	Five classes	Six statistical features	Back propagation neural network	95% obtained [46].
2012	eNTERFACE06 database for EEG data collection	Three classes	Features such as statistical, HOC, and wavelet entropy	k-Nearest Neighbor classifier (kNN)	90.77% obtained [48].

Year	Data collection	Emotions classification	Attributes extracted	Classifier used	Reported performance
2013	eNTERFACE06 database for EEG data collection	Two classes	Power Spectral Density (PSD), Short Time Fourier Transform (STFT) and Event Related Potential	ANN and Naïve Bayes classifier	Better performance above 80% [49] [50] [51] [52] [53].
2013	GenevaAffective Picture Database for EEG data collection	Two classes	Power spectrum from each band	support vector machine with 10 -fold cross validation	85.41% achieved [55].
2014	EEG data was collected by stimulating the subject with emotional movie clips	Two classes	Differential entropy	DBN-HMM, DBN, GELM, SVM, and KNN classifier	An accuracy of 87.62%, 86.91%, 85.67%, 84.08%, and 69.66% obtained [58].

Different methodologies were used by various researchers for studying and classifying emotions. Many features were extracted by different researchers in different domains. Time, frequency and statistical features were extracted in different studies [8, 39, 32, 46, 48, 50, 51, 55]. Wavelet transform by decomposing into five different frequency bands extensively used as a technique for feature extraction [33, 42]. Differential entropy was introduced by Shannon et al was used by various researchers for analyzing emotions [58]. SVM classifier was used in their studies for classification of emotions and it was seen that it achieved decent accuracy in properly classifying the emotions into different classes [32, 45, 55, 58]. Many researchers used artificial neural network as classifier and obtained considerably better accuracy [40, 33, 49, 50, 51, 52, 53]. Also, new technique of classification including Maximum a Posteriori (MAP) classification technique and DBM-HMM, DBN, GELM and k-nearest neighbor as classifier used by various researchers for recognition of emotions [8, 42, 43,44, 45,48, 58].

CHAPTER 4

METHODOLOGY

Five healthy, right handed male subjects with normal to corrected vision participated in the experiment for acquisition of EEG signal. The methodology followed for emotion classification is shown in the Figure 4.1.

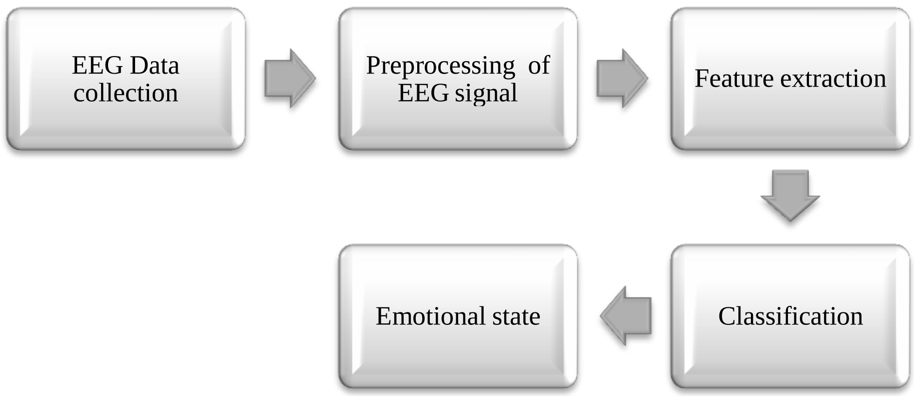


Figure 4.1: Different stages of methodology used

Data Collection

The EEG data has been collected by stimulating the subject with emotion evoking images from International Affective Picture System (IAPS) for classification of emotions into two classes. These images were collected by the scientists of National Institute of Mental Health Center for Emotion at University of Florida. The images belonging to High Valence High Arousal (HVHA) and High Valence Low Arousal (HVLA) are shown to the participants [59-61]. Images shown to participant are of every type such as nature, love, baby, snake, grave etc. The epoch time is selected to be of 2.5seconds. An image belonging to High Valence High Arousal is displayed for 1second followed by a plus symbol for 1.5seconds to have comfort of subject. Then next image corresponding to High Valence Low Arousal is shown to subject for 1 second followed by plus symbol for 1.5 seconds and vice versa. This EEG data has been acquired by placing a 20 electrode cap on the subjects head as per the international 10-20 system. To make contact between electrodes and the scalp, EEG gel is used in the electrodes. Using perfect synchronization between the presentation system and the data acquisition system, EEG data has been acquired from the subjects. The acquired raw EEG signal for one of the subjects is shown in Figure 4.2.

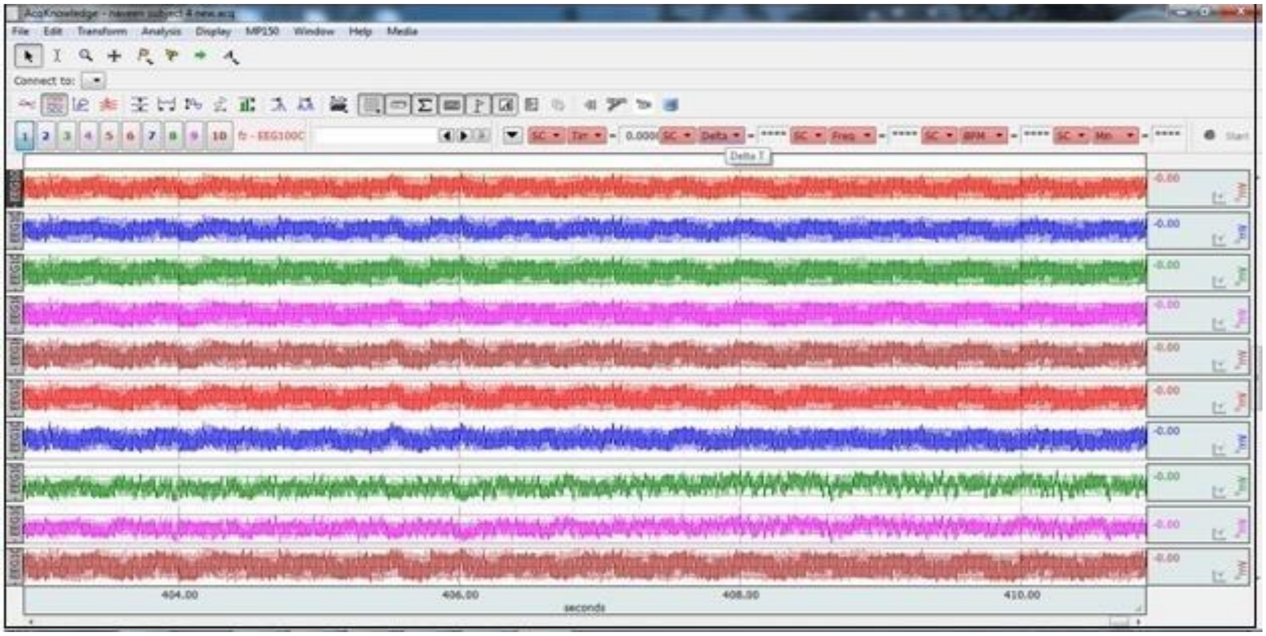


Figure 4.2: Acquired raw EEG signal on 10 Electrodes

Out of the 20 electrodes, three frontal electrodes namely F3, F4 and Fz electrodes are chosen for data processing and analysis. The EEG signals have been acquired at a sampling rate of 500 samples per second.

The recording equipment used for acquiring EEG signal is shown in Figure 4.3.

Figure 4.3: EEG Recording Equipment [62]

Hardware

The BIOPAC data acquisition unit MP150 interfaced with 20 electrode EEG cap is used to acquire EEG signals. The system consists of EEG gel to be used in electrodes, EEG amplifiers and earlobes attached to the participant. The EEG gel is filled into the electrodes with the help of a syringe. The level of the impedance is maintained below10 KOhm. The MP150 system consists of 10 bio amplifiers on to which the ten EEG electrodes can be connected to acquire the data in unipolar mode. Twenty electrodes can be connected to acquire data in bipolar mode. In our study the EEG data has been collected in unipolar mode. Data collection technique mainly involve of taking analog signal and converting into digital signal. The displayed converted signal on computer screen can be stored in a memory of computer which can be used for further assessment [63]. The acquired EEG signals are displayed on the system loaded with ACQ 4.2 Software provided by BIOPAC itself [64]. The emotions have been evoked using images from the IAPS dataset.

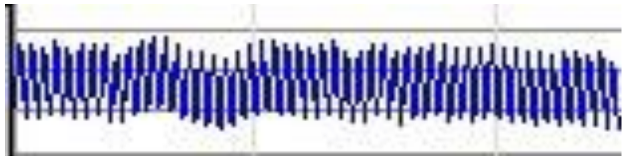
International Affective Picture System (IAPS)

It is widely used for classification of emotions because it provides stimulus to the subjects as described in our research review. This picture from the IAPS belongs are quantified along three axes namely Valence, Arousal and Dominance [65].

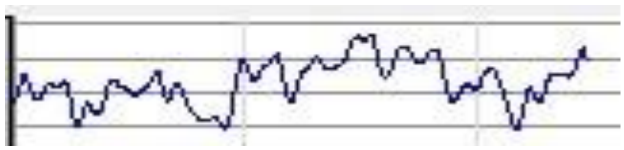
Preprocessing of EEG Signals

Signal preprocessing is very important aspect for obtaining better classification results. The acquired EEG data is preprocessed offline using the ACQ Software 4.2. The acquired EEG signal is preprocessed for removal of power noise to bring the signals in desired frequency range. The acquired EEG signals have been brought in the range of 0.5 to 40 Hz by using a low pass filter with a cut off frequency of 40Hz 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.

The acquired EEG signal before and after preprocessing is shown in Figure 4.4.



Before preprocessing of EEG signal



Preprocessed EEG signal

Figure 4.4: EEG signal before and After Preprocessing

Feature Extraction

After the conditioning of signal with various filters, the filtered data has been used for extracting various features. The attributes extracted for classification of emotions are Event Related Potential and Entropy.

Event Related Potential

Event Related Potential (ERP) is the first attribute which is extracted from the EEG data for emotion classification. A total of four attributes including latencies at which they occur are determined. The features that are extracted for emotion classification are P100, N100, PT100 and NT100. P100 is the max peak observed between 80ms to 120ms after the onset of stimuli, so P100 is considered as the maximum ERP of the subject in the time limit of 80 to 120ms. PT100 is the latency corresponding to the time (in ms) at which P100 occurs. N100 is min peak observed between 80ms to 120ms after the onset of stimuli, so N100 is considered as the minimum ERP of the subject in the time limit of 80 to 120ms. Similarly NT100 is the latency corresponding to the time (in ms) at which N100 occurs. Figure 4.5 shows the different ERP potentials.

Some of the features which have been extracted in this study are shown in Table 4.1.

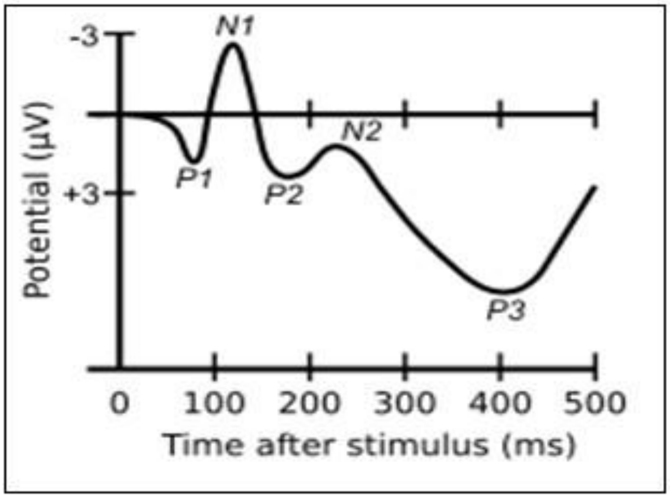


Figure 4.5: Event Related Potential [66]

Table 4.1 Extracted ERP features

P100	PT100	N100	NT100
-0.01525	80	-0.02401	0.116
0.00062	88	-0.00217	0.118
-0.0127	0.12	-0.0149	98
-0.00601	0.12	-0.01164	88
0.00629	84	-9.6E-05	0.12
0.02205	80	0.01583	0.12
-0.00167	80	-0.00214	0.12
-0.0055	82	-0.00686	0.1
0.00363	80	0.0003	0.12
0.00361	98	0.00144	80
0.01999	80	0.01307	0.12
-0.00078	0.12	-0.01504	80
0.01454	80	0.01403	88
-0.01912	80	-0.02191	0.102
0.00629	80	-0.00474	0.12
0.01791	80	0.01201	0.12
0.01896	0.106	0.01553	0.12
-0.0174	96	-0.01932	80
0.00934	0.11	0.00482	80
0.01668	80	0.01219	0.12
0.00575	0.108	0.00147	80
0.10411	0.114	0.10039	80
0.0092	80	0.00154	0.12
0.01189	80	0.00556	0.12
-0.01215	0.12	-0.01351	0.102
0.01483	0.12	-0.0051	86

P100	PT100	N100	NT100
0.00063	0.12	-0.00582	86
-0.00815	0.12	-0.00943	0.106
0.01836	80	0.01253	0.12
0.02743	86	0.02545	0.12
0.01436	80	0.00695	0.12
-0.00542	0.12	-0.00913	84
0.02559	0.12	-0.01241	80
0.00751	0.12	-0.00814	86
-0.00345	80	-0.00933	0.11
0.03368	82	0.02485	0.12
0.00377	88	-0.00457	0.12
0.02219	0.12	0.01446	80
0.01036	0.12	-0.00205	80
-0.01209	80	-0.02254	0.12
-0.00245	0.12	-0.00923	82
-0.00472	0.106	-0.00983	80
-0.00177	86	-0.00544	0.12
0.01747	80	0.01631	98
0.01215	0.12	-0.00194	80
0.00367	80	-0.00057	0.12
0.01118	80	0.00584	0.12
-0.00073	80	-0.00582	0.118
0.00072	0.118	-0.00452	84
0.00195	0.12	-0.00219	0.104
0.0076	80	0.00056	0.12
-0.00518	0.112	-0.00706	88
0.0288	80	0.01891	0.12
0.00134	80	0.00014	0.112
0.00071	86	-0.00499	0.118
-0.00286	0.12	-0.01253	80
0.01182	0.114	0.00835	84
0.00444	88	0.00326	0.12
0.00752	0.12	0.0028	80
0.00531	0.12	-0.00227	96
0.00634	80	-0.00029	0.12
-0.00447	0.1	-0.00695	0.12
-0.00176	80	-0.00935	0.118
-0.00034	0.102	-0.00365	0.12
0.00273	80	-0.00057	0.12
-0.00702	86	-0.01148	0.108
0.00562	82	-0.00118	0.11
-0.0019	0.112	-0.0113	80
0.02088	96	0.01452	80
-0.01482	80	-0.02345	0.116
0.00012	88	-0.00241	0.116

P100	PT100	N100	NT100
-0.01159	0.12	-0.01414	96
-0.00565	0.12	-0.0122	82
0.0049	86	-0.00083	0.12
0.02308	80	0.01703	0.12
-0.00252	0.114	-0.0032	94
-0.00578	82	-0.00674	98
0.00342	80	0.00076	0.12
0.00373	96	0.00127	80
0.02058	80	0.01291	0.12
-0.00188	0.12	-0.01526	80
0.01516	0.12	0.01396	86
-0.01952	80	-0.02318	0.102
0.00694	80	-0.00497	0.12
0.01763	80	0.01306	0.12
0.01934	0.108	0.01601	0.12
-0.0191	96	-0.02041	0.112
0.00912	0.112	0.00406	80
0.01741	80	0.01344	0.12
0.00578	0.11	0.00135	80
0.10595	0.114	0.10296	80
0.01004	80	0.00189	0.12
0.01155	0.1	0.00598	0.12
-0.01287	0.12	-0.01401	0.104
0.01495	0.12	-0.00525	88
0.00034	0.12	-0.00661	84
-0.00823	0.12	-0.0096	0.106
0.01835	80	0.01212	0.12
0.02881	86	0.0268	0.12
0.01451	80	0.00647	0.12
-0.00616	0.12	-0.00951	84
0.02681	0.12	-0.01299	80
0.00888	0.12	-0.0091	84
-0.00272	80	-0.00851	0.11
0.02978	82	0.02098	0.12
0.00487	90	-0.00373	0.12
0.02202	0.12	0.01473	80
0.01052	0.12	-0.00232	80
-0.01166	80	-0.02219	0.12
-0.00258	0.12	-0.00946	82
-0.00279	0.106	-0.00906	80
-0.00132	88	-0.00561	0.12
0.01904	80	0.01778	98
0.01366	0.12	-0.0016	80
0.00344	80	0.00039	0.102
0.01173	80	0.00575	0.12

P100	PT100	N100	NT100
-0.00107	80	-0.00635	0.116
0.00185	0.12	-0.00319	88
0.00185	0.12	-0.00256	0.104
0.00747	80	-0.00048	0.12
-0.00525	0.12	-0.00757	88
0.0288	80	0.0198	0.12
0.00052	80	-0.00072	0.112
0.00047	84	-0.00565	0.116
-0.00273	0.12	-0.01398	80
0.01245	0.114	0.00847	82
0.00545	80	0.00271	0.12
0.00723	0.12	0.00285	80
0.00423	0.12	-0.00221	96
0.00596	80	-0.00109	0.12
-0.00544	98	-0.00824	0.12
-0.00214	80	-0.01027	0.118
-0.00055	0.102	-0.00403	0.12
0.00289	80	-0.00075	0.12
-0.00668	86	-0.01171	0.108
0.00573	82	-0.0014	0.11
-0.00215	0.112	-0.01226	80
0.02161	96	0.01493	80
-0.0165	80	-0.0249	0.116
0.00085	88	-0.00196	0.116
-0.0127	0.12	-0.015	0.1
-0.00644	0.12	-0.01336	84
0.00552	86	-0.00023	0.12
0.02165	80	0.0159	0.12
-0.00202	0.112	-0.00272	94
-0.00619	82	-0.00704	98
0.00354	80	-0.00012	0.12
0.00387	98	0.00146	80
0.02082	80	0.01274	0.12
-0.00162	0.12	-0.01545	80
0.01523	0.1	0.01431	0.12
-0.02043	80	-0.02294	0.1
0.00526	80	-0.00633	0.12
0.01874	80	0.01351	0.12
0.01971	0.108	0.01623	0.12
-0.01793	98	-0.02006	80
0.00948	0.11	0.00436	80
0.01818	80	0.01335	0.12
0.00566	0.11	0.0012	80
0.10565	0.116	0.10329	82
0.01015	80	0.0015	0.12

P100	PT100	N100	NT100
0.01295	98	0.0068	0.12
-0.01255	0.12	-0.01411	0.1
0.01614	0.12	-0.00472	86
1.86E-05	0.12	-0.0068	86
-0.00866	0.12	-0.00981	0.106
0.01852	80	0.01238	0.12
0.02857	82	0.0264	0.12
0.01414	80	0.00595	0.12
-0.00589	0.12	-0.00978	84
0.02611	0.12	-0.01314	80
0.00754	0.12	-0.00976	80
-0.00344	80	-0.00912	0.11
0.03223	82	0.02263	0.12
0.00412	88	-0.00495	0.12
0.02261	0.12	0.01555	80
0.01099	0.12	-0.00188	80
-0.01299	80	-0.02387	0.12
-0.00329	0.12	-0.00969	82
-0.00405	0.106	-0.00945	80
-0.00247	92	-0.0063	0.12
0.01869	80	0.01716	98
0.01362	0.12	-0.00201	80
0.00337	80	-0.00048	0.12
0.01265	80	0.00653	0.12
-0.00051	80	-0.00639	0.118
0.00076	0.12	-0.00532	82
0.00217	0.12	-0.00168	0.106
0.00879	80	-0.00048	0.12
-0.00624	0.12	-0.00825	88
0.02868	80	0.01869	0.12
0.00271	80	0.00147	0.112
0.00027	86	-0.00537	0.118
-0.0035	0.102	-0.01331	80
0.01277	0.116	0.00887	84
0.00466	80	0.00339	0.12
0.00799	0.12	0.00319	80
0.00564	0.12	-0.00149	96
0.00676	80	-0.00066	0.12
-0.00389	0.1	-0.00735	0.12
-0.00235	80	-0.00923	0.118
-0.00111	0.1	-0.00451	0.12
0.00319	80	-0.00033	0.12
-0.00814	88	-0.01251	0.108
0.0053	82	-0.00249	0.11
-0.00247	0.112	-0.01245	80

P100	PT100	N100	NT100
0.0218	96	0.01476	80
0.00594	80	-0.00113	0.118
0.00334	98	-0.00247	0.118
-0.0025	0.104	-0.00438	82
0.00562	98	0.00149	80
0.00092	0.1	-0.00311	0.12
0.00196	0.104	-0.00052	86
0.00276	0.106	-0.00401	80
-0.00116	0.104	-0.00395	0.12
-0.00095	80	-0.00228	98
-0.00059	0.12	-0.00258	0.102
0.00082	80	-0.00402	0.104
0.00182	86	-0.00237	0.106
0.00484	0.106	-0.00204	88
0.00437	0.112	0.00039	80
0.00161	90	-0.00026	0.12
0.00024	80	-0.00375	0.106
0.00165	0.102	-0.00544	80
0.00184	0.116	-0.00321	98
0.00139	92	-0.00143	80
0.00264	0.102	-0.00082	80
0.00032	80	-0.00123	92
0.00145	0.12	0.00035	90
-0.00091	86	-0.00237	0.106
0.00248	80	0.00025	0.106
0.0006	80	-0.00539	0.118
0.00319	0.112	-0.00028	82
0.00039	0.108	-0.00157	0.12
0.00137	80	-0.00202	0.12
0.00157	0.12	-0.00166	80
0.0033	86	-0.00266	0.108
0.01234	0.12	-0.0021	0.1
0.00853	96	-0.00329	80
0.00349	0.12	-0.00361	80
0.00324	0.12	-0.00043	0.106
0.00392	0.114	0.00029	94
-0.00261	80	-0.00526	0.104
0.00429	80	0.00148	96
-0.00044	98	-0.00314	80
0.00566	0.112	0.00205	92
0.00072	0.112	-0.00359	94
0.00076	82	-0.00417	0.102
0.00046	80	-0.00241	92
-0.00062	0.108	-0.00479	86
0.0009	0.116	-0.00173	98

P100	PT100	N100	NT100
0.00617	90	-0.00438	0.116
-0.00109	84	-0.00192	98
0.00253	0.118	-0.00221	90
0.00218	86	-0.00049	0.12
0.00436	0.112	0.00096	92
0.00363	0.112	0.00057	90
0.00228	0.12	-0.00292	0.1
0.00224	88	-0.00347	0.108
0.00031	0.12	-0.00305	80
0.00488	0.11	0.00026	90
0.00278	0.106	-0.00278	88
0.00085	86	-0.00204	0.12
0.00041	0.11	-0.00511	90
0.00451	0.118	-0.00151	90
0.00136	96	-0.00381	80
0.00084	80	-0.0004	0.112
0.00293	0.12	-0.00081	88
0.00107	96	-0.00259	0.116
0.00044	98	-0.00221	80
0.00274	0.118	-0.00335	92
0.00259	94	-0.00176	0.112
0.00329	88	-0.00124	0.12
0.00406	98	-0.0011	80
0.00171	80	-0.00037	0.12
0.00272	0.116	-0.00173	98
0.00916	0.11	-0.00204	84
0.0027	0.102	-0.00117	80
0.0025	88	-0.00151	0.12
0.00471	0.12	0.0004	84
-0.00019	0.12	-0.00349	90
0.00646	80	-0.00989	0.118
0.00599	98	-0.00015	0.12
0.00471	80	-0.00161	0.12
0.00376	0.1	-0.00199	0.114
-0.00203	0.106	-0.00503	80
0.00622	94	0.00154	80
0.00141	96	-0.00299	0.12
0.00282	0.102	-0.00061	90
0.00348	0.106	-0.00365	80
-0.00051	0.106	-0.00457	0.118
-0.00072	0.12	-0.00308	94
-4.6E-05	86	-0.00266	96
0.00051	0.12	-0.00438	98
0.00276	86	-0.00183	0.1
0.00495	0.108	-0.00189	84

P100	PT100	N100	NT100
0.00476	0.11	0.00014	80
0.00179	94	-0.0003	0.12
-0.00016	80	-0.00414	0.102
0.0022	0.102	-0.00482	80
0.0021	0.116	-0.00298	96
0.00185	90	-0.00193	0.12
0.00239	0.1	-0.00152	80
0.00038	0.114	-0.00135	86
0.00131	0.106	7.33E-05	84
-0.00087	84	-0.00223	0.104
0.00235	0.12	0.0003	0.104
0.00088	80	-0.00561	0.118
0.00339	0.114	-0.00026	82
0.00026	0.11	-0.00213	0.12
0.0012	80	-0.00262	0.12
0.00104	0.12	-0.00219	0.1
0.00363	86	-0.00215	0.108
0.01229	0.12	-0.00204	98
0.00788	96	-0.00226	80
0.00495	0.12	-0.00346	80
0.00325	86	-4.8E-05	98
0.00485	0.112	0.00066	86
-0.00187	0.12	-0.0054	0.108
0.0045	82	0.00065	94
-0.0008	90	-0.00369	80
0.00659	0.11	0.00203	84
0.00091	0.114	-0.00344	90
0.00097	80	-0.00433	0.104
0.00014	80	-0.0025	88
-7.7E-05	0.106	-0.00405	90
0.0006	0.108	-0.00273	96
0.00672	92	-0.00364	0.118
-0.00084	0.116	-0.00243	0.104
0.00368	0.118	-0.0027	88
0.00267	88	-0.00118	0.12
0.00385	0.114	0.00022	90
0.00379	0.118	-6.4E-05	90
0.00267	0.118	-0.00241	94
0.00275	86	-0.00333	0.11
0.00047	0.12	-0.00266	80
0.00511	0.108	0.00032	0.12
0.00283	0.102	-0.00301	88
0.00101	90	-0.00326	0.12
0.0004	0.108	-0.00513	92
0.00532	0.118	-0.00202	88

P100	PT100	N100	NT100
0.00169	98	-0.00321	80
0.00111	0.12	-8.2E-07	82
0.00284	0.118	-0.00091	80
0.00152	96	-0.00243	0.114
0.00077	96	-0.00239	0.12
0.00274	0.118	-0.00343	90
0.00319	92	-0.00184	0.11
0.00331	88	-0.00161	0.12
0.00422	96	-0.00064	0.118
0.00148	80	-0.00057	0.12
0.00292	0.116	-0.00177	98
0.00923	0.108	-0.00227	84
0.00247	98	-0.00138	80
0.00234	88	-0.00213	0.12
0.00431	0.12	0.00024	80
-0.00026	0.12	-0.0031	92
0.00565	80	-0.01002	0.116
0.0059	98	0.00032	0.12
0.00494	80	-0.00143	0.12
0.00363	98	-0.00198	0.116
-0.00209	0.104	-0.00452	80
0.00546	94	0.00111	80
0.00119	96	-0.00347	0.12
0.0022	0.1	-0.00077	88
0.0031	0.104	-0.0034	80
-0.00062	0.104	-0.00415	0.118
-0.00073	80	-0.00261	92
-1E-04	84	-0.00228	96
0.00071	0.12	-0.00383	98
0.00251	86	-0.0017	0.104
0.00521	0.106	-0.00148	84
0.00492	0.108	0.00044	80
0.00162	92	-0.00077	0.12
-0.00035	80	-0.00414	0.102
0.00186	0.1	-0.00486	80
0.00202	0.114	-0.00289	98
0.00184	90	-0.00097	80
0.00235	0.102	-0.00134	80
0.00012	0.114	-0.00111	88
0.00139	0.12	0.00032	86
-0.00077	84	-0.0023	0.104
0.00237	0.12	0.00017	0.104
0.00094	80	-0.00534	0.118
0.00309	0.112	-0.00049	82
0.00057	0.11	-0.00194	0.12

P100	PT100	N100	NT100
0.00079	80	-0.00216	0.12
0.00134	0.12	-0.00202	80
0.00353	84	-0.00244	0.108
0.01247	0.12	-0.00223	98
0.0081	96	-0.00227	80
0.00478	0.12	-0.00327	80
0.00372	0.12	0.00012	0.108
0.00466	0.112	0.00076	96
-0.00191	0.12	-0.0053	0.106
0.00462	80	0.00124	94
-0.00078	90	-0.00308	80
0.00649	0.11	0.00281	92
0.00097	0.112	-0.00311	90
0.00079	80	-0.00447	0.102
-0.00026	80	-0.0024	88
-0.0005	0.104	-0.00444	88
0.00072	0.12	-0.00218	94
0.00684	90	-0.00409	0.116
-0.00113	0.114	-0.00212	0.104
0.00306	0.116	-0.00247	88
0.00237	86	-0.00108	0.12
0.00421	0.112	0.00042	88
0.004	0.116	0.00029	88
0.00253	0.118	-0.00276	0.102
0.00245	86	-0.00365	0.108
0.00064	0.12	-0.00254	80
0.00505	0.108	0.00019	90
0.00237	0.102	-0.00332	86
0.00128	86	-0.00272	0.12
0.00024	0.106	-0.00533	90
0.00469	0.116	-0.00175	86
-0.00012	98	-0.00437	0.12
0.00113	0.12	-0.00026	0.112
0.00287	0.118	-0.00043	88
0.00141	96	-0.00244	0.114
0.00061	96	-0.00235	0.12
0.0027	0.116	-0.00337	90
0.00283	92	-0.00164	0.11
0.00312	88	-0.00155	0.12
0.00378	96	-0.00084	0.116
0.00174	80	-0.00062	0.12
0.00287	0.116	-0.00188	98
0.00923	0.108	-0.00223	84
0.00245	0.102	-0.00139	80
0.00257	86	-0.00163	0.12

P100	PT100	N100	NT100
0.00463	0.12	0.0004	82
-0.00015	0.12	-0.00367	90
0.00549	80	-0.01014	0.116
0.00612	98	0.0002	0.12
0.00652	80	-0.00016	0.12
0.00193	0.104	4.87E-05	80
-0.00315	0.112	-0.00373	96
0.0044	0.114	0.00165	82
-0.00037	0.112	-0.00246	84
0.00182	80	0.00089	0.12
0.00036	0.114	-0.00274	88
-0.00058	80	-0.0024	0.12
-0.00081	80	-0.00194	0.114
-0.00126	0.12	-0.00185	94
0.00072	80	-0.0024	0.104
0.00097	80	-0.00071	0.106
0.00319	0.12	0.00063	86
0.00271	0.108	0.00082	80
0.00104	80	-0.00076	0.116
-0.00016	80	-0.00326	0.12
-0.00083	0.1	-0.0043	80
-6.8E-05	0.116	-0.0018	94
3.35E-05	0.102	-0.00115	80
0.0021	0.12	-0.00022	80
5.38E-05	80	-0.00065	0.1
0.00141	0.12	-4.7E-05	80
-0.00139	0.12	-0.00173	0.102
0.00161	84	0.00108	0.104
1.22E-06	80	-0.00417	0.116
0.00227	0.102	0.00092	80
-0.00031	94	-0.00171	0.118
5.66E-05	80	-0.00142	0.104
0.00023	0.108	-0.00121	84
0.00155	80	-0.00093	0.102
0.00824	0.12	-0.00068	80
0.00401	90	-0.00323	0.12
0.00765	0.12	-0.00169	80
0.00118	0.12	0.00033	80
0.00264	0.12	0.00129	80
-0.00284	82	-0.00437	0.112
0.00318	86	0.00254	0.102
-0.00142	80	-0.00175	88

Entropy

Entropy is the attribute which has been extracted from the preprocessed EEG data. EEG spectrum contains some characteristic waveforms that fall primarily with five frequency bands. Different researches give different ways to work on these bands, the bands chosen lies in the following frequency manner: delta (0-4 Hz), theta (4–8 Hz), alpha (8–16 Hz), beta (16–32 Hz) and gamma (32- 64Hz). Feature extracted from these sub bands of EEG signal is Entropy. It is considered as the strongest feature for emotion classification and defined as degree of randomness of signal [67]. Some of the features which have been extracted in this study for Entropy are shown in Table 4.2.

Table 4.2: Extracted Entropy Features

DELTA	THETA	ALPHA	BETA	GAMMA
0.10877	0.28928	0.5281	0.55514	0.57513
0.11933	0.36541	0.53341	0.5934	0.57632
0.1053	0.33343	0.50595	0.58162	0.60276
0.08623	0.36809	0.49421	0.57983	0.57653
0.12548	0.34103	0.46666	0.55288	0.5877
0.10819	0.32705	0.48972	0.55309	0.57553
0.14878	0.32081	0.48275	0.57999	0.59537
0.12569	0.33855	0.49302	0.56315	0.59573
0.11404	0.28302	0.52884	0.59702	0.54906
0.16546	0.37741	0.46934	0.57938	0.59625
0.09721	0.35884	0.49309	0.58309	0.57152
0.18073	0.42593	0.55768	0.5518	0.56507
0.10095	0.33375	0.49167	0.56743	0.57797
0.10582	0.35644	0.49019	0.59342	0.58682
0.17139	0.40161	0.52395	0.58873	0.58623
0.09932	0.35034	0.48456	0.56619	0.60159
0.18946	0.34633	0.48224	0.59261	0.60866
0.11752	0.33256	0.5372	0.56523	0.59322
0.16771	0.32023	0.4697	0.56584	0.58571
0.10069	0.29747	0.42885	0.55769	0.58589
0.07408	0.23987	0.45121	0.55552	0.57731
0.08269	0.25234	0.41774	0.59633	0.57936
0.09108	0.30322	0.44483	0.57139	0.59075
0.13677	0.31874	0.48808	0.58504	0.6053
0.08511	0.30659	0.47321	0.57759	0.58377
0.10086	0.31814	0.45832	0.53801	0.56277
0.09943	0.28702	0.46379	0.54857	0.59704
0.10978	0.27497	0.46978	0.57469	0.59157
0.1258	0.34936	0.44608	0.57633	0.55632
0.08386	0.27003	0.4145	0.57178	0.60765
0.10055	0.15704	0.3897	0.5508	0.57636
0.12359	0.34299	0.51831	0.57868	0.61872
0.13483	0.32837	0.43718	0.55198	0.58304
0.06436	0.29443	0.52152	0.58765	0.57699
0.10093	0.28987	0.4768	0.54498	0.5732

DELTA	THETA	ALPHA	BETA	GAMMA
0.08454	0.35972	0.38973	0.54665	0.53321
0.14365	0.20093	0.41345	0.52512	0.55432
0.18793	0.33725	0.55632	0.56611	0.58721
0.05479	0.37659	0.49802	0.5329	0.61092
0.12098	0.34562	0.52345	0.58342	0.6221
0.063	0.30098	0.4889	0.59671	0.5883
0.19834	0.22456	0.37789	0.61542	0.55521
0.10093	0.2759	0.53345	0.57423	0.57732
0.11683	0.36572	0.44476	0.54021	0.60018
0.09832	0.39552	0.47782	0.55986	0.60051
0.10932	0.3387	0.43365	0.58007	0.58832
0.13334	0.38773	0.51156	0.51227	0.58876
0.14879	0.40921	0.48898	0.5165	0.55782
0.06734	0.25343	0.45981	0.55672	0.59032
0.17653	0.28973	0.54769	0.57633	0.60123
0.11132	0.29873	0.48921	0.5854	0.5749
0.10092	0.29002	0.50932	0.58983	0.63321
0.08761	0.33871	0.54654	0.60064	0.53998
0.10933	0.37801	0.43476	0.54329	0.59002
0.16753	0.31864	0.46022	0.58809	0.52119
0.09321	0.24374	0.51299	0.54465	0.63321
0.0772	0.30113	0.44882	0.55743	0.58871
0.19202	0.38832	0.47368	0.57689	0.5221
0.17632	0.20093	0.54532	0.61123	0.54423
0.08432	0.22198	0.4508	0.56673	0.55533
0.14504	0.33998	0.49202	0.57411	0.57766
0.1229	0.36709	0.49562	0.52289	0.59902
0.11765	0.39665	0.51123	0.52002	0.5498
0.18998	0.39821	0.43234	0.54098	0.61123
0.04532	0.43276	0.38456	0.57822	0.59823
0.10437	0.26658	0.34579	0.57932	0.54432
0.17399	0.27765	0.41123	0.52033	0.57649
0.0854	0.33456	0.46092	0.54901	0.58876
0.11132	0.36114	0.54986	0.56633	0.53387
0.10095	0.33815	0.51975	0.59874	0.52219
0.19976	0.27763	0.49922	0.55439	0.51155
0.14981	0.29474	0.44666	0.51209	0.58662
0.13675	0.37654	0.53386	0.53467	0.59933
0.11131	0.27615	0.51601	0.56153	0.56508
0.109	0.35346	0.50112	0.56509	0.55913
0.12752	0.32436	0.54104	0.57361	0.58762
0.11626	0.34263	0.51015	0.58286	0.58063
0.11621	0.36561	0.45898	0.5633	0.57601
0.08737	0.30902	0.50115	0.55914	0.56202
0.08591	0.22287	0.4475	0.5387	0.58132
0.14355	0.32942	0.48501	0.55803	0.59731
0.11445	0.3446	0.48691	0.55994	0.60588
0.10085	0.35487	0.46321	0.54929	0.60443
0.09439	0.36155	0.52449	0.57832	0.55352
0.18638	0.40922	0.52059	0.57827	0.61464
0.10855	0.30338	0.46089	0.56651	0.58191

DELTA	THETA	ALPHA	BETA	GAMMA
0.10978	0.3865	0.52147	0.56799	0.58447
0.11464	0.33937	0.527	0.57925	0.59642
0.08511	0.40199	0.51561	0.57951	0.60722
0.19367	0.33933	0.50476	0.6089	0.58234
0.11038	0.35118	0.49339	0.62338	0.58548
0.11467	0.31498	0.50039	0.55702	0.579
0.11708	0.32717	0.45376	0.58136	0.57928
0.07808	0.26081	0.48939	0.5819	0.58935
0.08955	0.28244	0.42381	0.5676	0.58046
0.07353	0.33172	0.4927	0.55573	0.58247
0.13681	0.36193	0.49024	0.60666	0.60424
0.0785	0.26354	0.48164	0.57204	0.58918
0.09827	0.31734	0.51251	0.59883	0.58437
0.08744	0.30993	0.47663	0.57182	0.60084
0.0786	0.29944	0.45542	0.56797	0.59106
0.08114	0.30288	0.40454	0.54848	0.55828
0.08997	0.28347	0.4519	0.57959	0.56129
0.10503	0.26418	0.45693	0.5448	0.56964
0.12565	0.36855	0.49666	0.58417	0.59079
0.12996	0.33983	0.43709	0.56789	0.59082
0.0778	0.28578	0.4913	0.57062	0.58015
0.12048	0.32176	0.53637	0.57264	0.55256
0.09742	0.29765	0.4781	0.57365	0.5609
0.11347	0.29317	0.45978	0.55487	0.58833
0.11998	0.38053	0.49581	0.57043	0.58325
0.09634	0.37763	0.4962	0.58168	0.59055
0.10604	0.32295	0.47584	0.58148	0.57867
0.09526	0.33941	0.4592	0.56475	0.57552
0.15201	0.30663	0.48662	0.5547	0.58342
0.1028	0.32663	0.49061	0.58671	0.59337
0.05466	0.34683	0.44402	0.5279	0.59498
0.14029	0.32723	0.51312	0.59343	0.59356
0.12999	0.39034	0.49568	0.57501	0.5506
0.06412	0.39784	0.54752	0.55911	0.61521
0.17567	0.37312	0.50262	0.57772	0.62072
0.09361	0.30869	0.48856	0.59166	0.57219
0.17978	0.3915	0.49268	0.58076	0.60196
0.11668	0.25118	0.49282	0.56562	0.58027
0.08555	0.35319	0.48279	0.61909	0.57939
0.13541	0.35782	0.52147	0.56191	0.56912
0.10936	0.31588	0.47406	0.59608	0.60605
0.09325	0.34912	0.49326	0.58761	0.60018
0.08464	0.33921	0.4547	0.58913	0.59554
0.0649	0.20836	0.39722	0.56129	0.583
0.13379	0.32428	0.4887	0.55285	0.5356
0.07889	0.32349	0.46326	0.57512	0.59864
0.12517	0.30587	0.46547	0.58433	0.60801
0.06839	0.31383	0.46837	0.56457	0.56715
0.10499	0.33836	0.51045	0.55351	0.5827
0.05349	0.37572	0.48859	0.58572	0.56923
0.07676	0.18959	0.35783	0.51717	0.58451

DELTA	THETA	ALPHA	BETA	GAMMA
0.0922	0.33103	0.48921	0.56941	0.55951
0.0776	0.39465	0.42165	0.54798	0.59535
0.09619	0.26465	0.35511	0.55745	0.58899
0.19555	0.3319	0.5132	0.55173	0.57459
0.06115	0.37316	0.5292	0.50645	0.55246
0.09176	0.28116	0.51048	0.56203	0.56233
0.12352	0.27608	0.43123	0.57493	0.59896
0.18166	0.34539	0.458	0.54993	0.59436
0.10577	0.38425	0.49002	0.60123	0.60434
0.08875	0.24452	0.43234	0.57188	0.61502
0.12335	0.4609	0.5421	0.60678	0.64121
0.08253	0.38642	0.43865	0.58247	0.66725
0.10538	0.37592	0.55739	0.52864	0.58428
0.1154	0.41655	0.54661	0.56025	0.63741
0.12745	0.24846	0.56493	0.54396	0.66438
0.10043	0.44682	0.42864	0.58473	0.59438
0.09438	0.36581	0.53852	0.60538	0.62854
0.14386	0.33629	0.55835	0.58539	0.65386
0.08369	0.40579	0.43752	0.59364	0.61437
0.10047	0.4411	0.56386	0.54852	0.60365
0.21849	0.45682	0.51739	0.61587	0.63982
0.1196	0.24375	0.49562	0.58442	0.66323
0.09438	0.35042	0.53072	0.56798	0.58327
0.11735	0.40494	0.43002	0.60113	0.60482
0.21953	0.39403	0.55721	0.58553	0.64372
0.12846	0.31538	0.48326	0.56379	0.59732
0.05782	0.45942	0.56482	0.64332	0.58002
0.11345	0.39001	0.5128	0.53841	0.61863
0.15478	0.36723	0.56389	0.57323	0.63489
0.11039	0.3147	0.44732	0.64392	0.64389
0.14893	0.45003	0.51936	0.59435	0.66341
0.07346	0.38145	0.48903	0.60221	0.58392
0.12064	0.40038	0.55482	0.54511	0.63562
0.21608	0.40949	0.48009	0.57667	0.59458
0.1002	0.43895	0.53842	0.58033	0.60481
0.17375	0.35284	0.46538	0.64863	0.58391
0.13842	0.38549	0.49539	0.60582	0.68392
0.08451	0.3385	0.55631	0.54735	0.62725
0.14197	0.34555	0.53117	0.56116	0.61893
0.10345	0.36892	0.42276	0.61482	0.58492
0.18112	0.35145	0.53027	0.54847	0.59523
0.09356	0.38947	0.43896	0.52458	0.64864
0.1081	0.34604	0.53845	0.57534	0.61648
0.10045	0.44744	0.55487	0.61287	0.59836
0.18348	0.24876	0.42454	0.59821	0.64538
0.09385	0.38829	0.53782	0.57878	0.58463
0.11368	0.45511	0.57632	0.60438	0.64539
0.14628	0.36001	0.59321	0.54587	0.61386
0.17369	0.45701	0.54421	0.59871	0.65487
0.11584	0.41188	0.45325	0.64378	0.66319
0.08462	0.40881	0.58451	0.57688	0.61266

DELTA	THETA	ALPHA	BETA	GAMMA
0.11732	0.39722	0.59881	0.62254	0.58975
0.18493	0.43842	0.53256	0.58763	0.65438
0.11063	0.44921	0.56471	0.59976	0.64881
0.10043	0.33854	0.53002	0.57658	0.67549
0.17353	0.37862	0.46739	0.61243	0.57649
0.11063	0.26571	0.51472	0.60987	0.59766
0.15369	0.28432	0.58943	0.55687	0.63754
0.11973	0.31952	0.52401	0.58809	0.5883
0.07352	0.38897	0.58006	0.60952	0.62339
0.14369	0.35485	0.46592	0.54986	0.66754
0.21853	0.44365	0.51359	0.57631	0.57002
0.11548	0.35559	0.59432	0.5987	0.6439
0.18392	0.3423	0.53342	0.64328	0.61033
0.08362	0.37692	0.55639	0.61733	0.65221
0.19438	0.39591	0.53456	0.59804	0.59879
0.11003	0.41275	0.45602	0.56821	0.68098
0.10583	0.44529	0.49832	0.63492	0.64329
0.11847	0.40984	0.58402	0.61809	0.5987
0.15475	0.28578	0.53453	0.59577	0.63208

Classification

After the extraction of features from preprocessed data, the EEG data has been used for classification of emotions into two classes' namely High Valence High Arousal and High Valence Low Arousal along arousal axis. The classification refers to the process of distinguishing to which category a new observation belong, based on training set of data consisting instances whose category membership has been known. Classifier has been used for classification. Classifier refers to the mathematical function which is employed by algorithm and maps input data into a particular category. In this study the classifier used is LIBSVM [68].

LIBSVM

The classification has been performed using LIBSVM classifier with 3 fold cross validation and RBF kernel. LIBSVM is software that is being used for support vector classification, distribution estimation and regression. It has various features like efficient multi-class classification, cross-validation for the selection of best model, availability of various inbuilt kernels like linear kernel, polynomial kernel, RBF kernel etc. The support-vector network is the learning machine for classifying the data in two groups. The conceptual idea implemented by the machine is that the input vectors are mapped non-linearly into a very large dimension feature space. The linear decision surface is being constructed in the feature space. High generalization ability of the support vector machine is ensured by this decision surface [69]. Figure 4.6 shows the basic classification criteria of support vector machine.

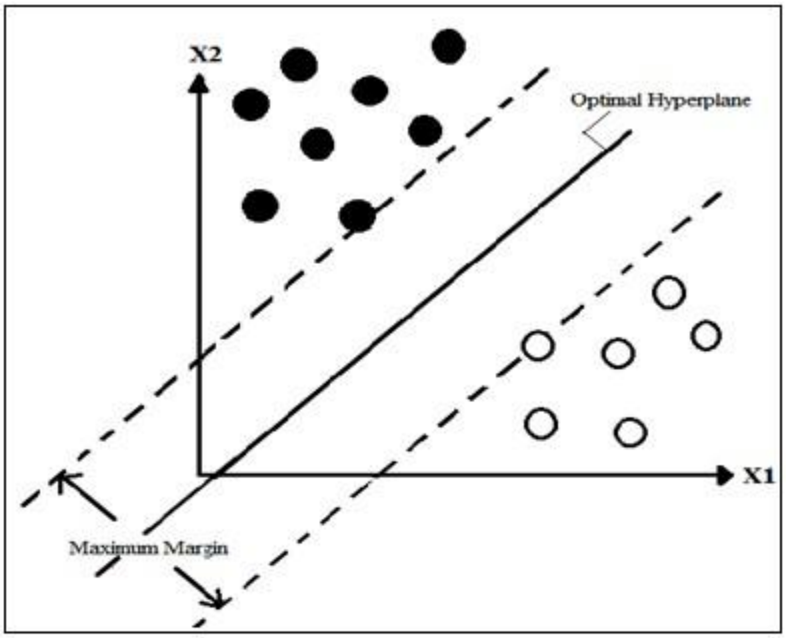


Figure 4.6: General Support Vector Classifications

These classifiers are applied in MATLAB for classifying the signals. Classification accuracy is then calculated accordingly depending upon how many signals are classified correctly.

LIBSVM Instructions

The various MATLAB instructions used for LIBSVM classifier are summarized in the Table 4.3.

Table 4.3: MATLAB Instructions used

Instructions	Use
svmtrain	svmtrain(training_label_vector,training_instance_matrix,'libsvm_options')
svmpredict	svmpredict(testing_label_vector,testing_instance_matrix, model, 'libsvm_options')

CHAPTER 5

RESULTS AND DISCUSSION

The extracted attributes are used to classify emotions into two classes namely High Valance High Arousal and High Valence Low Arousal. The attributes such as Event Related Potential and Entropy has been used to determine the accuracy of data. Training and testing is performed on each subject for different combinations of attributes extracted by using LIBSVM classifier with RBF kernel and 3 fold cross validation. The training is performed on 70% of samples of each subject. Best values of cost factor and gamma is determined and the best model is developed for the subject under observation. This model is tested on test samples (remaining 30%) of that subject.

Classification

Using Event Related Potential attributes

The analysis has been done on three frontal electrodes namely Fz, F3 and F4. The Event Related Potential attributes is extracted from five subjects. The Table 5.1 shows highest classification accuracy at F3, F4 and Fz electrode.

Table 5.1: Classification accuracy on frontal electrodes with ERP attributes

Subjects	Highest accuracy of F3 electrode (%)	Highest accuracy of F4electrode (%)	Highest accuracy of FZ electrode (%)	Best accuracy
Subject 1	73.68	68.42	68.42	73.68
Subject 2	70.80	79.16	70.83	79.16
Subject 3	70.80	75	70.83	75
Subject 4	73.07	76.92	73.07	76.92
Subject 5	76.19	71.42	71.42	76.19

For subject 1 it can be seen that best accuracy of 73.68% has been achieved across F3 electrode when taking all attributes namely P100, Pt100, N100 and Nt100. In the same way for F4 and Fz electrode accuracy obtained is 68.42% when taking particular bio potential with corresponding latency. When considering subject 2 under concern it can be seen that best accuracy of 79.16% has been obtained across F4 electrode as compared to F3 and Fz electrode.

In the same way for subject 3, maximum accuracy achieved is 75% for F4 electrode as compared to Fz and F3 electrode which is 70.80%. Also for subject 4, maximum accuracy of 76.92% is achieved across F4 electrode. But in case of subject 5, maximum accuracy achieved is across F3 electrode which is 76.19% and for F4 and Fz electrode accuracy achieved is 71.42%. The best accuracy obtained is shown in Figure 5.1.

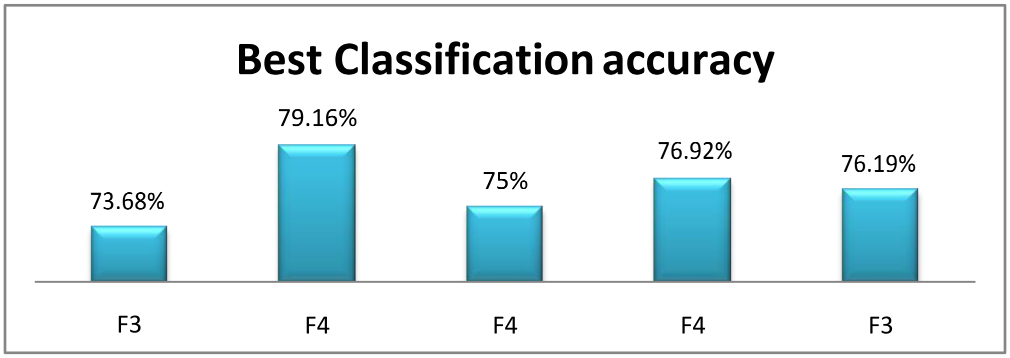


Figure 5.1: Classification Accuracy for Best Electrode

The electrode with best accuracy of 79.16% along F4 electrode has been obtained when subject wise classification is performed. The subject wise ranking of the electrodes namely Fz, F3 and F4 is shown in Table 5.2:

Table 5.2: Ranking of electrodes

Subjects	F3	F4	Fz
Subject 1	1st	3rd	2nd
Subject 2	2nd	1st	2nd
Subject 3	3rd	1st	2nd
Subject 4	2nd	1st	2nd
Subject 5	1st	2nd	2nd

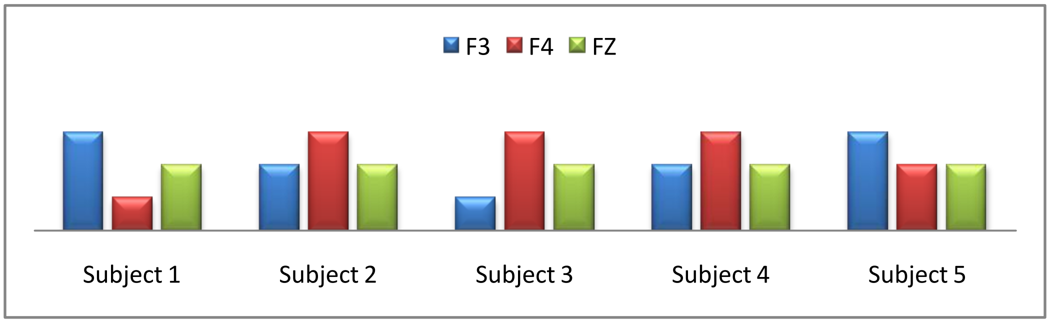


Figure 5.2: Subject wise ranking of electrode

It shows that classification of emotions along the arousal axis can be best performed on F4 electrode then F3 electrode followed by Fz electrode from ranking Figure 5.2. An accuracy of 79.16% has been achieved across F4 electrode which is highest among F3 and Fz electrode.

Further the data has been analyzed to determine the best attribute for subject 1 to subject 5. The classification has been performed on eleven combinations of the four attributes namely (P100,Pt100), (P100,N100), (P100,Nt100), (Pt100,Nt100), (N100,Nt100), (N100,Pt100), (P100,Pt100,N100), (P100,Pt100,Nt100), (Pt100,N100,Nt100), (P100,N100,Nt100) and (P100,Pt100,N100,Nt100). The classification accuracy at F3 electrode for 11 attribute combinations is shown in Table 5.3.

Table 5.3: Classification accuracy at F3 electrode for 11 attributes combinations

Subjects	**Classification accuracy at F3 electrode for 11 attribute combinations**										
	P100-Pt100 (%)	P100-N100 (%)	P100-Nt100 (%)	Pt100-Nt100 (%)	N100-Nt100 (%)	N100-Pt100 (%)	P100-Pt100-N100 (%)	P100-Pt100-Nt100 (%)	Pt100-N100-Nt100 (%)	P100-N100-Nt100 (%)	P100-Pt100-N100-Nt100 (%)
Subject 1	52.63	57.89	68.42	57.89	63.15	57.89	73.68	73.68	57.89	52.63	73.68
Subject 2	62.5	54.16	66.66	62.5	58.3	70.8	66.66	62.5	66.66	58.3	66.66
Subject 3	58.33	63.5	66.66	68.32	62.5	58.33	54.16	70.8	66.66	62.5	62.5
Subject 4	53.84	46.15	53.84	59.83	63.33	57.69	57.69	61.5	53.8	57.6	73.07
Subject 5	66.66	57.14	61.90	61.90	66.66	76.19	66.66	61.90	66.66	57.80	76.19

It can be seen from Table 2 that at F3 electrode for different attribute combinations, the best accuracy of 73.68% has been achieved for attribute combinations (P100, Pt100, N100, Nt100), (P100, Pt100, N100) and (P100, Pt100, Nt100) in case of subject 1. In the same way for subject 2, the best accuracy of 70.80% has been obtained for attribute combination (N100, Pt100). For subject 3, the best accuracy achieved for attribute combination (P100, Pt100, Nt100) is 70.8% and for subject 4, an accuracy of 73.07% has been achieved for attribute combination (P100, Pt100, N100, Nt100). In the same way, for attribute combination (P100, Pt100, N100, Nt100), (N100, Pt100), the best accuracy of 76.19% has been obtained for subject 5. The classification accuracy at F4 electrode for 11 attribute combinations is shown in Table 5.4.

Table 5.4: Classification accuracy at F4 electrode for 11 attributes combinations

Subjects	Classification accuracy at F4 electrode for 11 attributes combinations										
	P100-Pt100 (%)	P100-N100 (%)	P100-Nt100 (%)	Pt100-Nt100 (%)	N100-Nt100 (%)	N100-Pt100 (%)	P100-Pt100-N100 (%)	P100-Pt100-Nt100 (%)	Pt100-N100-Nt100 (%)	P100-N100-Nt100 (%)	P100-Pt100-N100-Nt100 (%)
Subject 1	57.8	57.89	66.66	67.89	63.15	68.4	57.8	52.6	63.15	63.15	57.8
Subject 2	62.5	66.66	79.16	62.5	62.5	54.16	75	62.56	66.66	75	66.66
Subject 3	62.5	70.88	62.5	70.83	58.33	75	62.66	66.66	68.26	62.5	66.66
Subject 4	76.92	69.23	65.38	65.38	61.5	65.38	57.69	65.38	61.5	69.23	72.03
Subject 5	66.66	61.90	71.4	57.14	71.42	66.66	61.9	57.14	61.9	57.14	64.15

The best accuracy has been achieved along attribute combination (N100, Pt100) is 68.4% for subject 1. For subject 2, the highest accuracy of 79.16% has been obtained for attribute combination (P100, Nt100). In the same way, the best accuracy achieved for attribute combination (N100, Pt100) is 75% for subject 3. The best accuracy of 76.92% has been obtained in case of subject 4 for attribute combination (P100, Pt100). In case of subject 5, an accuracy of 71.42% has been achieved for attribute combination (P100, Nt100) and (N100, Nt100). The classification accuracy at Fz electrode for 11 attribute combinations is shown in Table 5.5.

Table 5.5: Classification accuracy at Fz electrode for 11 attributes combinations

Subjects	Classification accuracy at Fz electrode for 11 attribute combinations										
	P100-Pt100 (%)	P100-N100 (%)	P100-Nt100 (%)	Pt100-Nt100 (%)	N100-Nt100 (%)	N100-Pt100 (%)	P100-Pt100-N100 (%)	P100-Pt100-Nt100 (%)	Pt100-N100-Nt100 (%)	P100-N100-Nt100 (%)	P100-Pt100-N100-Nt100 (%)
Subject 1	52.63	52.63	68.42	57.89	63.15	57.89	63.15	63.15	63.15	57.89	57.8
Subject 2	62.5	58.33	62.5	62.5	66.66	58.33	62.5	70.83	62.5	66.66	62.5
Subject 3	62.5	70.88	58.33	62.5	66.66	58.33	61.5	62.5	66.66	58.3	70.8
Subject 4	61.5	57.89	65.38	73.07	69.23	53.28	57.69	65.38	57.89	61.5	61.5
Subject 5	71.42	61.90	66.66	66.66	61.9	71.42	71.42	57.14	61.9	57.14	61.9

The best accuracy of 68.42% has been achieved for attribute combination (P100, Nt100) in case of subject 1. In the same way for subject 2, the accuracy of 70.83% has been obtained for attribute combination (P100, Pt100, Nt100). For subject 3 the best accuracy achieved for attribute combination (P100, Pt100, N100, Nt100) and (P100,N100) is 70.80%. An accuracy of 73.07% has been obtained for attribute combination (Pt100, Nt100) in case of subject 4. In the same way for subject 5, the accuracy obtained for attribute combination of (P100, Pt100), (N100, Pt100) and (P100, Pt100, N100) is 71.42%. When average of 11 different attribute combination extracted from four attributes is performed, the best accuracy obtained is shown in Figure 5.3.

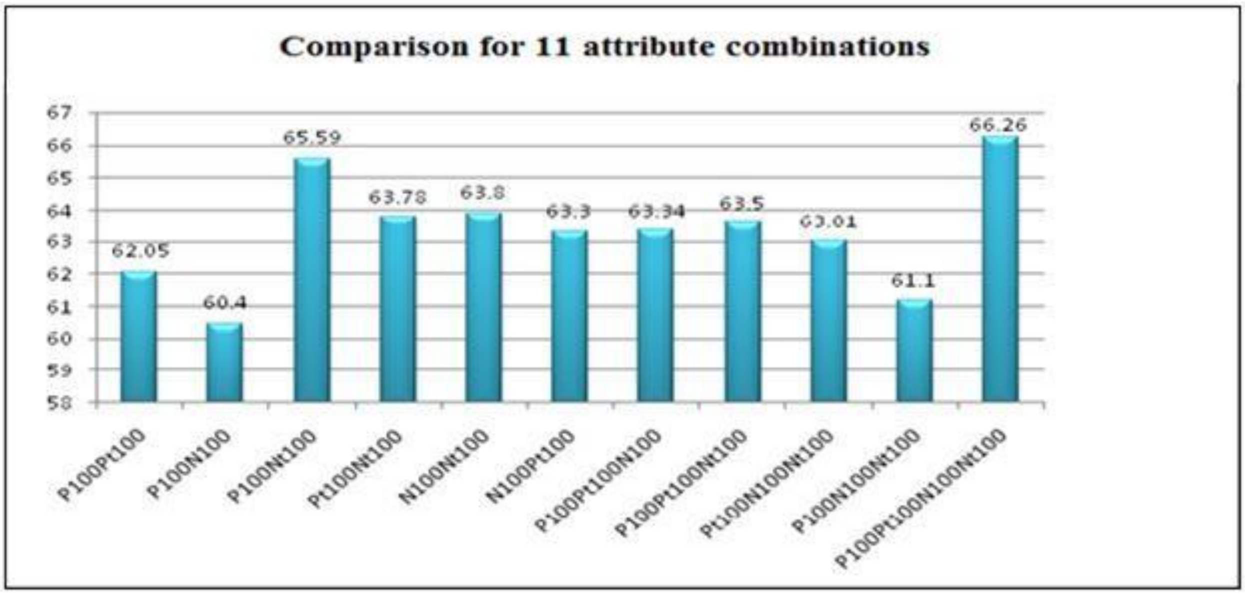


Figure 5.3: Classification accuracy of 11 attributes combinations

It can be seen that the best accuracy has been obtained for (P100, Pt100, N100, Nt100) followed by (P100, Nt100) and (N100, Nt100). An accuracy of 66.26% has been achieved for (P100, Pt100, N100, Nt100), 65.59% for (P100, Nt100), 63.89% for (N100, Nt100).

It shows that for the ERP attributes P100, N100, Pt100 and Nt100; the attribute combination (P100, Pt100, N100, Nt100) comes out to be the best parameter for classifying emotions along the arousal axis.

Using Entropy attributes

The Entropy attribute is extracted from three subjects on F3 and F4 electrode. The EEG data is decomposed into five different frequency bands namely delta (0-4 Hz), theta (4–8 Hz), alpha (8–16 Hz), beta (16–32 Hz) and gamma (32- 64Hz) by using filtering technique. The entropy attribute has been extracted for every class of emotions from the five frequency bands. The classification has been performed on six combinations of the five sub bands such as delta, theta, alpha, beta, gamma of EEG signal. The Entropy determined in delta band is represented by E_d, theta band by E_t, alpha band by E_a, beta band by E_b and gamma band by E_g. The classification accuracy at F3 and F4 electrode for subject 1 is shown in Table 5.6.

Table 5.6: Classification accuracy for subject 1 with Entropy attributes

Subject 1		
Entropy combination	**Accuracy at F3 electrode (%)**	**Accuracy at F4 electrode (%)**
E_d E_t E_a E_b E_g	62.5	58.89
E_d E_t E_a E_b	58.33	46.77
E_t E_a E_b E_g	54.16	58.33
E_d E_a E_b E_g	58.88	58.88
E_d E_t E_a E_g	45.83	57.14
E_d E_t E_b E_g	41.88	45.38

It can be seen for subject 1, when taking all entropy combinations acquired by decomposing an EEG signal into five frequency bands, an accuracy of 62.5% has been obtained for F3 electrode and 58.89% for F4 electrode. In the same way when entropy determined by taking alpha beta theta delta combinations of EEG signal, an accuracy of 58.33% has been obtained for F3 electrode, 46.77% for F4 electrode. An accuracy of 54.16 has been obtained for F3 electrode and 58.33% for F4 electrode when entropy combination such as alpha beta theta gamma is taken under observation. For the entropy combination namely alpha beta delta gamma of EEG signal, an accuracy of 58.88% has been achieved for F3 and F4 electrode. In the same way an accuracy of 45.83% for F3 electrode and 57.14% for F4 electrode has been achieved when entropy is determined by taking alpha theta delta gamma combination of EEG signals. When entropy combination such as beta theta delta gamma of EEG signal is taken, an accuracy of 41.88% for F3 electrode and 45.38% for F4 electrode has been obtained. Figure 5.4 shows classification accuracy for subject1.

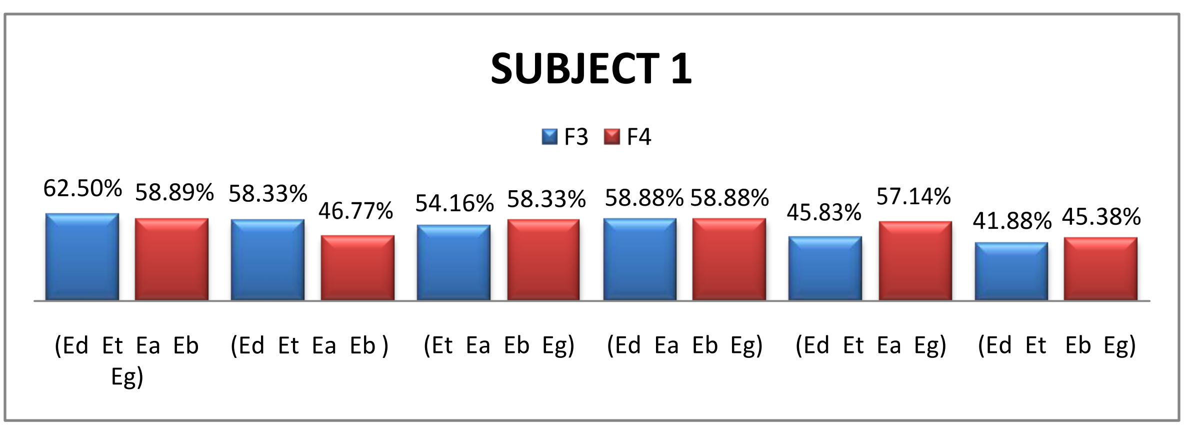


Figure 5.4: Classification accuracy of Subject 1 for different Entropy combinations

It can be seen that the best results are obtained when considering all five frequency bands of EEG signal for subject1.

In the same way for subject 2, the best accuracy of 63.42% has been achieved for F3 and 66.66% for F4 electrode when all entropy combinations acquired by decomposing an EEG signal into five frequency bands are considered. The classification accuracy at F3 and F4 electrode for subject 2 is shown in Table 5.7.

Table 5.7: Classification accuracy for subject 2 with Entropy attributes

Subject 2		
Entropy combination	**Accuracy at F3 electrode (%)**	**Accuracy at F4 electrode (%)**
E_d E_t E_a E_b E_g	63.42	66.66
E_d E_t E_a E_b	61.9	52.38
E_t E_a E_b E_g	66.66	57.14
E_d E_a E_b E_g	57.42	57.14
E_d E_t E_a E_g	61.90	61.9
E_d E_t E_b E_g	59.89	41.38

From Figure 5.5 it can be seen that the best results are obtained when considering all five frequency bands of EEG signal for subject 2.

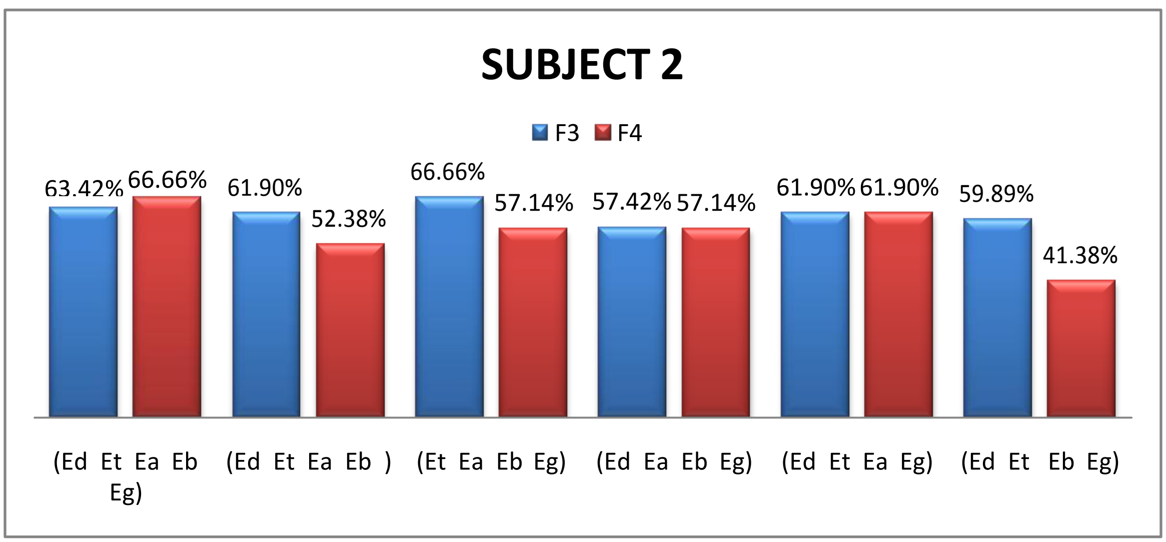


Figure 5.5: Classification accuracy of Subject 2 for different Entropy combinations

For subject 3, better results has been obtained by taking all band combinations with highest accuracy achieved up to 68.5% for F3 electrode and 66.66% for F4 electrode. The classification accuracy at F3 and F4 electrode for subject 3 is shown in Table 5.8.

Table 5.8: Classification accuracy for subject 3 with Entropy attributes

Subject 3		
Entropy combination	**Accuracy at F3 electrode (%)**	**Accuracy at F4 electrode (%)**
E_d E_t E_a E_b E_g	68.5	66.66
E_d E_t E_a E_b	54.16	52.38
E_t E_a E_b E_g	45.83	57.14
E_d E_a E_b E_g	57.14	57.14
E_d E_t E_a E_g	61.90	45.38
E_d E_t E_b E_g	41.88	61.9

From Figure 5.6 it can be seen that the best results are obtained when considering all five bands of EEG signal for subject3.

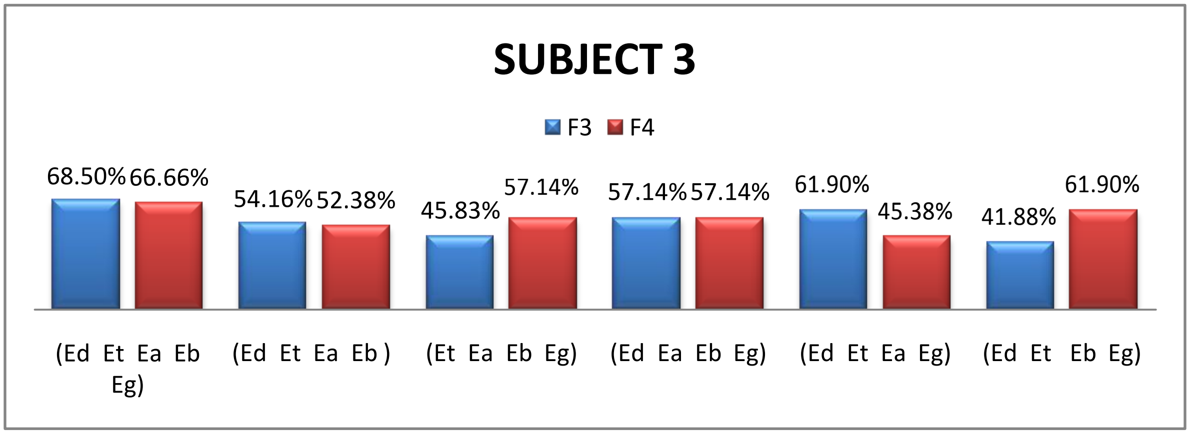


Figure 5.6: Classification accuracy of Subject 3 for different Entropy combinations

It can be seen from Figure 5.7 when all five frequency bands of EEG signal are compared for every subject along F3 and F4 electrode, the accuracy is remaining in the range nearly 60% to 70%. The highest accuracy has been obtained along F3 electrode followed by F4 electrode as shown in Figure 5.7. An accuracy of 68.50% has been achieved along F3 electrode, 66.66% for F4 electrode.

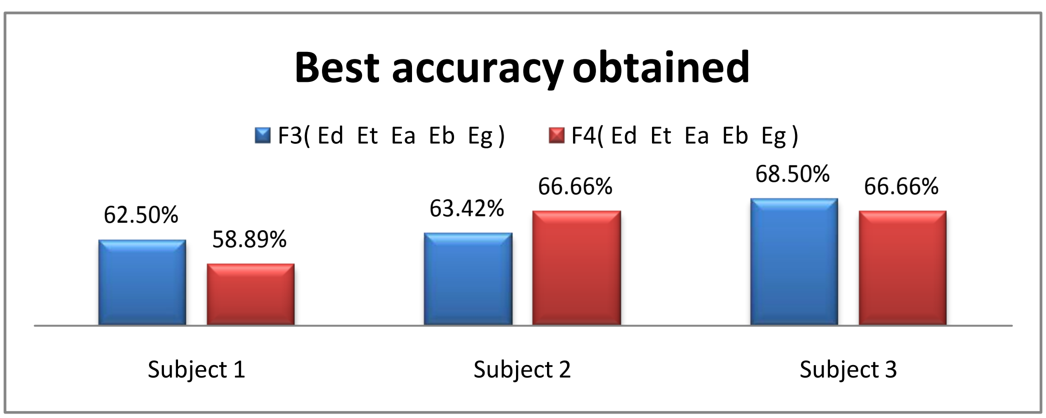


Figure 5.7: Best classification accuracy obtained Subject wise

It shows that classification of emotions along the arousal can be performed best when combination of entropies extracted from all five frequency bands are used for classification.

Comparison of Results obtained with ERP and Entropy attributes

When both the attributes namely Event related potential and Entropy is compared for classification of emotions. The classification accuracy obtained for ERP as attribute is shown in Table 5.9.

Table 5.9: Classification accuracy obtained with Event Related Potential attributes

Subjects	Highest Accuracy of electrodes (%)		
	F3 Electrode	**F4 Electrode**	**Best accuracy**
Subject 1	73.68	68.42	73.68
Subject 2	70.80	79.16	79.16
Subject 3	70.80	75	75

It can be seen that when extracted attribute Event related potential is taken, it has been found that an accuracy of 73.68% is achieved at F3 electrode and 68.42% at F4 electrode for subject 1. In the same way for subject 2, an accuracy of 70.80% has been obtained at F3 electrode and 79.16% at F4 electrode. For subject 3, an accuracy of 70.80% has been obtained at F3 electrode, 75% at F4 electrode. It shows that highest accuracy of 79.16% has been obtained which is consistently high among other subjects. Thus accuracy obtained for all subjects is highest when emotions are classified along arousal axis with ERP attribute.

In the same way, the extracted attribute Entropy by decomposing the EEG signal into five frequency bands is considered for classification of emotions. It has been found out that accuracy obtained is comparatively lower than ERP at F3 and F4 electrode when individual subject for classification is considered. The classification accuracy obtained for Entropy as attribute is shown in Table 5.10.

Table 5.10: Classification accuracy obtained with Entropy attributes

Subjects	**Highest Accuracy of electrodes (%)**		
	F3 Electrode	**F4 Electrode**	**Best accuracy**
Subject 1	62.5	58.89	62.5
Subject 2	63.42	66.66	66.66
Subject 3	68.5	66.66	68.5

It shows that highest accuracy of 68.5% has been obtained which is consistently high among other subjects for Entropy attribute

It can be seen that highest accuracy among all subjects has been achieved for event related potential attribute. Whereas for extracted attribute Entropy, it can be seen that accuracy obtained is comparatively low among all subjects. The classification accuracy obtained with different attribute is shown in Table 5.11.

Table 5.11: Comparison of classification accuracy obtained with different features

Features used for classification	**Subject 1**	**Subject 2**	**Subject 3**
Event related potential	73.68	79.16	75
Entropy	62.5	66.66	68.5

It can be seen that the accuracy achieved is far better for extracted attribute Event related potential than Entropy when emotions are classified into two classes along arousal axis. The best classification accuracy obtained subject wise on comparing both of attributes is shown in Figure 5.8.

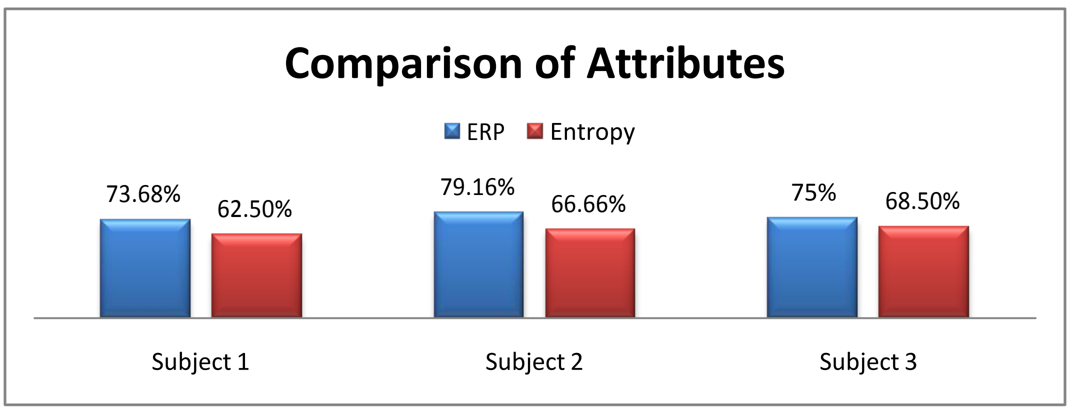


Figure 5.8: Comparison of ERP and Entropy attributes

CHAPTER 6

CONCLUSION AND FUTURE SCOPE

Emotions are necessary to understand the behavior of an individual. In this dissertation, data has been acquired from Electroencephalogram (EEG) signals on frontal electrodes namely Fz, F3 and F4 to develop a two class emotion classifier. The acquired EEG is preprocessed for every class of emotions. The entropy attribute five frequency bands and ERP potentials such as P100, N100 and the two latencies corresponding to these bio potentials has been extracted from preprocessed EEG signals. The classification has been performed using LIBSVM classifier with 3 fold cross validation and RBF kernel to classify emotions along the arousal axis. When ERP potential is used for classification of emotions, it has been found that accuracy remains consistently high on F4 electrode. An accuracy of 79.16% has been obtained on F4 electrode, 76.19% on F3 electrode and 73.07% on FZ electrode when classifying emotions subject wise. Among the eleven attribute combinations used in this study for ERP attribute, (P100, Pt100, N100, Nt100) is found to be the best combination as accuracy remained consistently high for this combination on all electrodes. The average classification accuracy with this combination comes out to be 66.26%. It is further noticed that by reducing the number of attributes, the classification accuracy decreases. However if we take (P100, Nt100) the classification accuracy is 65.59% which is marginally lower. Hence we may go in for this combination as well if computational time is restricted. Further when Entropy attributes from five frequency bands of EEG signal is used for classification of emotions; it has been found that among the six combinations used in this study, E_d E_t E_a E_b E_g is the best combination. The accuracy of classification along arousal axis achieved is 68.50% at F3 electrode and 66.66% at F4 electrode when all five frequency bands of EEG signal are considered. When the comparison of different attributes namely Event related potential and Entropy has been performed. The accuracy of classification is consistently better in all three subjects for event related potential than entropy. It has been observed that ERP for subject 1, subject 2 and subject 3 is classified effectively with an accuracy of 73.68%, 79.16% and 75% respectively. Whereas accuracy achieved for Entropy for all the three subjects is not so good.

Future Scope

No study is complete in itself; there is always a scope for improvement. In this dissertation only four attributes namely: P100, Pt100, N100 and Nt100 have been extracted for emotion classification. By considering more number of ERP features and subjects, the scope could be widened. Since three frontal electrodes have been used for classification, more number of electrodes can be considered. Furthermore data has been classified into two classes, so classification of emotions can be performed into four classes to improve results.

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