DEVELOPMENT OF EEG BASED EMOTION CLASSIFIER

A Thesis Submitted By

Moon Inder Singh

Registration No.: 951104002

For the Award of Degree of

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Under the Supervision of

Dr. Mandeep Singh

Associate Professor

Electrical and Instrumentation Engineering

Department

THAPAR INSTITUTE
OF ENGINEERING & TECHNOLOGY

(Declared as Deemed-to-be-University u/s 3 of the UGC Act., 1956)

Punjab (India)-147004

DECLARATION

I hereby declare that the research work presented in this thesis entitled "Development of EEG based emotion classifier" in partial fulfillment of the requirement for the award of the degree of Doctor of Philosophy and submitted in the Department of Electrical and Instrumentation Engineering, Thapar Institute of Engineering and Technology, Patiala is an authentic record of my own work carried out under the supervision of Dr. Mandeep Singh, Associate Professor, Department of Electrical and Instrumentation Engineering. The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other Institute.

Moon Inder Singh

Moon Inder Singh

Date: 24/8/18

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

Supervisor

Dr. Mandeep Singh
Associate Professor
Department of Electrical and Instrumentation Engineering
Thapar Institute of Engineering and Technology, Patiala

Date: 24/8/18

DEDICATED TO

My late father, Sh. Gurdeep Singh who was a thorough gentleman and an educationist.

My revered mother, Smt. Amarjit Kaur who in her declining years wished and prayed to see her sons get doctorate in her life time.

My affectionate, caring and loving better half, Kulveen Kaur for her persistent and unconditional support during, before and after the period of my research work.

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" Vidia vichari taan parupakari Jan panch rasi tan tirath vasi...

Ghungharu vajai je manu lagai Tau jamu kaha kare mo siu agai..1.. Rahau"

If thou art to deliberate over thy knowledge, only then wilt thou become the benefactor of all. When thou controls thine five evil passions, then, shalt thou become the dweller at the pilgrimage station. If the mind is fixed, then that is the tinkling of small bells. Then, what can the death's courier, do unto me, hereafter? Pause. (Verses by Guru Nanak)

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LIST OF PUBLICATIONS FROM PRESENT WORK

1) Singh MI and Singh M (2017) Development of low-cost event marker for EEG-based emotion recognition. *Transactions of the Institute of Measurement and Control*, SAGE Publications Sage UK: London, England 39(5): 642–652.

2) Singh MI and Singh M (2017) Development of a real time emotion classifier based on evoked EEG. *Biocybernetics and Biomedical Engineering*, Elsevier B.V 37(3): 498-509.

ABSTRACT

Analysis and study of abstract human relations have always posed a daunting challenge for technocrats engaged in the field of psychometric analysis. The study on emotion recognition is all the more demanding as it involves integration of abstract phenomenon of emotion causation and emotion appraisal through physiological and brain signals. Emotion is most commonly defined as short and intense reaction of humans occurring on account of a stimulus. Occurrence of emotion may bring a noticeable change in physiological parameters such as respiration rate, heart rate, Galvanic Skin Resistance (GSR), body temperature and ElectroEncephaloGram (EEG) etc. Changes in physical parameters such as color of the skin, eye gaze, eye blink rate and shape of the face are also perceived. The study of complex human emotions for developing an affective Brain Computer Interface (BCI) has for long been an area attracting biomedical scientists. Moreover emotion recognition plays an important role for all the personnel involved in mission critical tasks like for pilots, nuclear plant operators and air traffic controllers etc.

The challenge to develop an affective BCI demanded understanding of emotions psychologically, physiologically as well as analysis from engineer's point of view. To make the analysis and classification of emotions possible, emotions have been represented in a 2-dimensional or 3-dimensional space represented by arousal and valence domains or arousal, valence and dominance domains respectively. Interestingly, the classification of emotions along any of the domains is possible by utilizing the orthogonal nature of emotions. One of the effective ways to classify emotions is by use of Event Related Potential (ERP) of EEG signals. This requires projection of emotion evoking stimulus on one computer system while simultaneously putting a mark on another computer system acquiring EEG. It is generally achieved by using costly modules to synchronize stimulus presentation system with the data acquisition system. Apart from emotion recognition system, this study describes an innovative low cost technique to achieve simultaneous triggering on the second computer system using parallel operation of mechanical keyboards. The latency aspect of both USB and PS/2 keyboards with their two keys galvanically connected have been experimentally analyzed and compared. The synchronization error between the two USB keyboards has been

found to be lower than or equal to 1 millisecond for nearly 70% of keystrokes. Even in the worst case the synchronization error does not exceed 8 millisecond. Our window of ERP is ±20 millisecond and hence the error of this magnitude is acceptable. The use of this synchronization setup has saved expenditure to the tune of $3000.

EEG signals have been acquired from 24 right handed male subjects to classify emotions into four classes, namely low valence high arousal (LVHA), high valence high arousal (HVHA), high valence low arousal (HVLA) and low valence low arousal (LVLA). For emotion evocation, the visuals from International Affective Picture System (IAPS) have been used. For each class of emotion, 40 IAPS images classified on the basis of arousal and valence on a scale of 1 to 9 have been used with an epoch time of 2.5 second. The evoked EEG signals have been acquired in a unipolar mode on 10 Ag/AgCl electrodes namely Fp1, Fp2, F3, F4, F8, Fz, Cz, Pz, P3 and P4 at a sampling frequency of 500 samples per second by using Biopac MP150 system and EEG100C EEG cap.

Emotion classification using EEG signals can primarily be done either in offline mode by taking average of EEG signals acquired from several trials or in online mode by taking a single trial. In this study, emotion classification has been obtained by taking both the cases into consideration viz; by using single trial and average of EEG signals. The single trial ERP features have been used for both subject dependent and subject independent emotion classification whereas average ERP features have been used for subject independent emotion classification. Apart from ERP features, the difference of ERPs both average and single trial have been used to develop subject independent four class emotion classifiers. In other words, five categories of four class emotion classifier have been developed and reported in this study, namely, subject dependent emotion classifier using single trial ERP features (accuracy 68.2%), subject independent emotion classifier using single trial ERP features (accuracy 39%), subject independent emotion classifier using difference of single trial ERP features (accuracy 55%), subject independent emotion classifier using average ERP features (accuracy 83%) and subject independent emotion classifier using difference of average ERP features (accuracy 77%). In all cases we have considered self assessment as gold standard for training, testing and validation of four class emotion classifier.

We have found that the subject independent emotion classifier using average ERPs has the best accuracy of 83%. The results are better as compared to the existing study on average ERPs. The existing study on average ERPs reported four class emotion classification accuracy in the range of 68 - 82% with mid range accuracy of 75% whereas in the proposed classifier, the four class emotion classification accuracy lies between 82% - 88% with mid range of 85%. The proposed classifier is better in performance on account of electrode selection, order of Support Vector Machine (SVM) polynomial classifier and feature reduction.

It is prudent to mention here that the subject dependent emotion classifier requires training each time the subject is to be tested for emotion because of the day to day variations in external and internal conditions. This limits its practical utility. The subject independent classifier is trained by collecting several trials on different days from large number of subjects possessing unique behavior and personality. Thus a subject independent classifier once trained would have more practical utility in classifying emotions without the need of training again before testing on subjects.

The advantage of single trial emotion recognition is instantaneous result, while in offline mode; it takes several minutes to reach any conclusion. Since emotion is a short lived phenomenon, assuming that this remains the same for several minutes of data acquisition, may be erroneous. This at best would give the average emotional state. However, the four class classification accuracy using average and difference of average ERP attributes is much higher as compared to the accuracies obtained using single trial modes. This is due to the fact that averaging eliminates the noise interference in signals. To improve the accuracy results using single trial EEG, difference of single trial ERP attributes for classification of emotions have been proposed in this study. Taking a difference of local maxima and minima (maximum ERP and minimum ERP) acquired within the fixed latency period eliminates the common noise affecting the acquired signal. This is evident from the emotion classification results obtained on difference of single trial ERP attributes.

Apart from the development of emotion classifier, an intervention technique has been applied on 20 right handed male subjects. These 20 subjects had been found to be in LVHA state of emotion using self assessment and EEG classifier. Intervention was given to these 20 subjects with an aim to bring them to HVLA state. Of the 20 subjects, 16 could comply with the intervention and reported through self assessment the transition to HVLA state. Application of a four class subject independent emotion classifier validated 13 of 16 subjects in HVLA state.

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LIST OF ABBREVIATIONS AND SYMBOLS

GSR	Galvanic Skin Resistance
EEG	ElectroEncephaloGram
BCI	Brain Computer Interface
ERP	Event Related Potential
LVHA	Low Valence High Arousal
HVHA	High Valence High Arousal
HVLA	High Valence Low Arousal
LVLA	Low Valence Low Arousal
IAPS	International Affective Picture System
IADS	International Affective Digital Sounds
SVM	Support Vector Machine
EMG	ElectroMyoGram
MEG	MagnetoEncephaloGram
PPG	PhotoPlethysmoGraph
ECG	ElectroCardioGram
TEAP	Toolbox for Emotional feAture Extraction
Acq	AcqKnowledge
fNIRS	Functional Near- Infrared Spectroscopy
MA	Mean Arousal
MV	Mean Valence
SAM	Self Assessment Manikin
DaFeX	Database of Kinetic Facial Expressions
DEAP	Database for Emotion Analysis using Physiological Signals
BVP	Blood Volume Pulse
EOG	ElectroOculoGram
RBF	Radial Basis Function
HCI	Human Computer Interface
CSD	Current Source Density
MNS	Mirror Neuron System
HOC	Higher Order Crossing
QDA	Quadratic Discriminant Analysis
KNN	k-Nearest Neighbor
MD	Mahalanobis Distance
RPE	Recoursing Power Efficiency
LRPE	Logarithmic Recoursing Power Efficiency
ALRPE	Absolute Logarithmic Recoursing Power Efficiency
RFE	Recursive Feature Elimination
ICA	Independent Component Analysis
GNB	Gaussian Naïve Bayes
mRMR	Min-Redundancy-Max-Relevance
PCA	Principal Component Analysis

LDA	Linear Discriminant Analysis
KFEP	Kernel Fisher's Emotion Pattern
I-SVM	Imbalanced Support Vector Machine
IQK-SVM	Imbalanced Quasiconformal Kernel Support Vector Machine
LSTM-RNN	Long Short Term Memory Recurrent Neural Network
MLR	Multi Linear Regression
SVR	Support Vector Regression
CCRF	Continuous Conditional Random Field Models
APCC	Average Pearson Correlation Coefficient
RMSE	Root Mean Square Errors
GAPED	Geneva Affective Picture Database
LOTO-CV	Leave-One-Trail-Out Cross-Validation
LOSO-CV	Leave-One-Subject-Out Cross-Validation
MCA	Multimedia Content Analysis
MFCC	Mel-Frequency Cepstral Coefficients
EM	Experienced Meditators
NM	Novice (non-experienced) Meditators
MSTN	Mental Transition State Network
HMRE	Human Emotion Recognition Engine
MECE	Machine Emotion Creation Engine
FACS	Facial Action Coding System
SE	Synchronization Error
LP	Latency for the Positive ERP
LN	Latency for the Negative ERP
CFAPS	Chinese Facial Affective Picture System
VPP	Vertex Positive Potential
DBN	Deep Belief Networks
HMM	Hidden Markov Model
ICI	Incorrect Classified Instances
CCI	Correctly Classified Instances
P100 N100 P200 N200 P300 N300 PT100 NT100 PT200 NT200 PT300 NT300	ERP Features
Fz, Cz, Pz, Fp1, Fp2, F3, F4, P3, P4 and F8	EEG Electrodes Used
F5	Function Key of Keyboard
δ	Delta Band (0-4Hz)
θ	Theta Band (4-7Hz)
α	Alpha Band (8-12Hz)
β	Beta Band(12Hz-30Hz)
γ	Gamma Band (More than 30Hz)
dT	Time Uncertainty

CHAPTER-1

INTRODUCTION AND LITERATURE SURVEY

1.1 Introduction to Emotions

At the very outset it is imperative to define and review the phenomenon under analysis in the research undertaken. Since the current research focuses on analysis of human emotions hence, it is incumbent to define the various attributes of emotions and reactions thereof. The subject of social psychology focuses on emotional behavior and social cognition. The social-psychological investigation using electrical and electronic instrumentation requires that the psychological aspect under study should be delineated and defined properly as far as possible. Different theorists have defined cause and effect of emotions differently. The social psychologists argue that the perception, memory, problem solving, judgment and task performance etc. are immensely influenced by emotion (Scherer, 2000). Breckler and Wiggins (1993) has averred that emotions also play an important role in attitudinal changes. Clearly, it is really interesting to comprehend the emotional signaling through expressive behavior. Further, several psychologists have propounded that emotions play a major role in establishing and nurturing social relationships such as friendship and marriages (Berscheid, 1991; Gottman, 1994; Brody, 2009). Thus obviously emotion is a central pillar upholding the social-psychological phenomenon. The dependency of human life more on emotions than on physical comforts makes it necessary to study emotions. Before proceeding further it would be prudent to define emotion. William James revered as father of experimental psychology contended in 1884 that the bodily changes follow directly the perception of the exciting fact, and that our feelings of the same changes as they occur is the emotion. Carl Lange in 1885 propounded a similar model of emotion with the same causal sequence as James had laid out. However, the theories proposed by James and Lange have been criticized and improved upon by many present and past researchers (prominent being Cannon (1927)) by contending that the occurrence of emotion in fact causes physiological changes. Accordingly emotion is defined as a phenomenon that describes the reaction of a person in response to an event or a stimulus. The stimulus acts as an input to the human brain, which makes a person experience different feelings like joy, anger, love, hate, horror, etc. The emotions are generally short and intense, and occur on account of the presence of stimulus (Moors, 2009). It is very widely admitted that modern day researchers and scholars do not agree on the definition of emotions. For example, Kleinginna and Kleinginna (1981) collected and analyzed 92 definitions of emotion from literature present in that period and concluded that emotion arises due to activation of a neural/hormonal system in response to some happening that makes us experience a feeling of excitement, pleasure or displeasure, while simultaneously causing a change in physiological variables and affecting our behavior. However, Frijda (1986) viewed that it was not at all possible to define emotions correctly prior to the empirical research. Reisenzein (2007) goes to the extent of saying that a proper definition of emotion is not at all necessary for fruitful research and analysis and concludes that emotion is a mental state and is in the same class as sensations, beliefs and desires.

Several psychologists have suggested a different number of the basic emotional states, ranging from two to 18 categories, but there has been a considerable agreement on the following six: anger, disgust, fear, happiness, sadness and surprise. Plutchik (1962) considered eight basic states of emotions – as anger, fear, sadness, disgust, surprise, curiosity, acceptance and joy – to be elementary ones, whereas Ekman (1999) considered five emotion states – fear, sadness, happiness, disgust and surprise – as the basic ones.

To recognize emotions different researchers have tried to obtain the relationship between psychological behavior and physiological signals. Cannon (1927) described that, in humans, emotions occur with changes in physiological variables such as muscular tension, a rise in heart rate, perspiration and dryness of the mouth owing to certain external stimuli. Cacioppo and Tassinary (1990) obtained the relations between psychological operations and physiological responses, called psycho-physiological relations. Lang et al. (1993) discovered that the mean value of the galvanic skin resistance is related to the level of arousal. Moreover, blood pressure and heart rate variability are variables that correlate with defensive reactions and pleasantness of a stimulus (Chanel et al., 2007).

Emotions are often expressed through various gestures like smiling, frowning, clenching of jaws etc., which involve several muscular activities. It is often said in stress management workshops that it takes 17 muscles to smile and 42 to frown. Irrespective of the authenticity of number of muscles required, activity of muscles for recognizing emotions cannot be undermined. This muscular activity can be monitored by recording an ElectroMyogram (EMG) of the subject under observation (Healey, 2000). The initial computers took input from human beings in the form of keystrokes on a keyboard. Later advances started recognizing speech through microphones. Still later, even eyeball tracking through cameras was used to understand the expressions in humans to some extent. Emotions have been studied by researchers developing hi-tech computer interfaces, to enhance mental abilities and even to enhance physical abilities of humans (Ebrahimi et al., 2013; Luini and Marucci, 2015; Vast et al., 2010). It has been found that the patients with access to brain–computer interface technology recover more quickly from serious mental traumas, especially if a stroke like a paralytic attack renders the patient incapable of communicating (Graimann et al., 2010).

1.2 Necessity of Studying Emotions

The necessity of detecting and classifying emotions can be highlighted from the following:

1) Better human machine interaction i.e. machines to recognize human emotions: The whole exercise about having artificial intelligence in machines is to make machines behave more like humans. The human being is not just an intellectual entity but an emotional being as well. In cases where machines are able to detect and classify human emotions, they will definitely make better companions (Picard, 2000).
2) Objectively check the efficacy of mood-altering drugs: mood-altering and habit-forming drugs like stimulants, opiods, sedative hypnotics and hallucinogens are highly addictive and need to be prescribed with caution. The dosage needs to be regulated as per emotional requirements which can be objectively quantified using an emotional classifier (Vaccarino and Rotzinger, 2004).

3) Screen out mission critical personnel for emotional effects: it can be described with an example that the pilot of an airliner in a bad mood may be a risk to many lives. If we have an emotion classifier based on physiological parameters like EEG, then all mission critical personnel may be asked to undergo this test in a manner similar to a breath test analyser.
4) Prevent cases of rage: to prevent incidents such as shootings at universities due to stress, road rage and high altitude defense personnel shooting their own colleagues, it becomes imperative to check the chances of depression.
5) Objectively check the efficacy of non-pharmaceutical interventions: The efficacy of non-pharmaceutical interventions like meditation, aromatherapy, yoga etc. can be effectively analysed using an EEG-based classifier (Herz, 2009; Speca et al., 2000). To sum up, it can become a useful means of detecting and controlling negative emotions that may lead to depression, performance hindrance, marital discord, mass murders, rapes, abusive and bullish behaviour, and even suicides.

1.3 Tools used for Studying Emotions

The acquisition of physiological signals for classification of emotions is in vogue. Various types of signals from different parts of human body such as signals from muscles using EMG systems, brain signals using EEG, MagnetoEncephaloGram (MEG) etc., heart rate using chest straps or PhotoPlethysmoGraph (PPG) based pulse sensors (from finger tip), ElectroCardioGram (ECG) for measuring heart rate activity, Ag/AgCl electrodes for measuring skin conductance, eye tracking using eye glasses, facial expressions (2d/3d) using cameras/ video recorders and audio signals etc. are being acquired, preprocessed and analyzed individually or in fusion, be it at feature level or decision level using state of the art classification and processing techniques. The acquisition of emotional sensitive physiological signals and then extracting classifiable attributes both in time and frequency domains is in fact a cumbersome job. The acquisition of signals requires hardware that may be invasive or non-invasive and the processing requires software tools working individually or in MATLAB platform. For example, open source processing tools such as EEG LAB (Delorme and Makeig, 2004), Toolbox for Emotional feAture Extraction (TEAP) (Soleymani et al., 2017) are some of the tools that work in MATLAB platform and are used for processing of acquired physiological signals (Pratibha et al., 2017). Most of the tools help in offline processing of physiological and EEG signals except the licensed software(s) purchased along with the proprietary equipments such as Biopac. Though the list of these packets (software and hardware) which enable real time acquisition and processing is large, Biopac provided AcqKnowledge 4.X is one such licensed software that is purchased along with the Biopac provided compatible devices. We used Acq Knowledge 4.2 along with EEG 100C cap for acquisition of EEG data, filtering operations and extraction of attributes. For offline analysis, we used EEG Lab (Delorme and Makeig, 2004) for analyzing eNTERFACE 2006 data (savran et al., 2006; Surbhi et al., 2013). The Emotiv devices along with the compatible software are also common among researchers. However, open ViBE (Please see openvibe.inria.fr/discover/. for more information) is another open source platform recommended by brain scientists for real time acquisition, processing and classification of brain signals but the compatibility with the hardware systems is an issue. For offline processing, another software platform namely EDF browser (Please see https://www.teuniz.net/edfbrowser/EDFbrowser%20manual.html for further information) which is open source and can be used for processing of various physiological signals such as EEG, EMG and ECG. Apart from EEG Lab and EDF browser, BCI LAB (open source MATLAB tool box), Brainstorm (Tadel et al., 2011), Fieldtrip (Oostenveld et al., 2011) etc. are open source software's commonly used for analysis of brain signals. We recommend the readers to go through the link https://www.biosemi.com/download.htm for more details.

The analysis of emotions along different co-ordinates (2d, 3d etc.) involves acquisition of EEG and physiological signals on one computer system with emotion evoking stimulus such as pictures, audio, video or combination of these presented to the subjects on the 2nd computer system. Suitable presentation systems as well as combination of hardware and software systems are being used for time locking (synchronization) of physiological/ body signals with emotion evoking stimulus. The presentation systems such as PsychoPy (www.psychopy.org), OpenVibe (openvibe.inria.fr), Presentation System (www.neurobs.com) or even Matlab can be used for presenting emotion evoking stimulus with high precision (mostly in milliseconds or even better) and recording the triggers causing change in stimulus. This helps in time locked acquisition of data. We used Presentation Software (Version 18.0, Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com) for our own experimentation involving emotion evocation and EEG signal acquisition.

1.4 Database of Physiological Signals for Emotion Recognition

Since our study is focused on analyzing EEG signals for emotion recognition, we are presenting the brief information about some of the databases which primarily includes EEG data apart from other physiological signals and are being used by researchers in their studies.

1.4.1 eNTERFACE 06 Database

After each eNTERFACE workshop, the participants under the group leader share the data collected, codes developed, results obtained and solutions as well as observations related to a problem publicly in a MIT like open source code. In a workshop held in the year 2006 (Dubrovnik, Croatia), one of the projects undertaken was to perform "Emotion detection in the loop from brain signals and facial images". In this project Savran et al. (2006) acquired brain activity using Functional Near- Infrared Spectroscopy (fNIRS), face video, brain signals using EEG and peripheral signals such as respiration rate, cardiac rate, and GSR with the primary objective of creating a multimodal database that could be used in future for validating and detecting emotions with different modalities (fusion of data at different levels). Savran et al. made a significant statement that due to the interactions of emotions with external environment, the difference in occurrence of claimed emotions may occur. The signals from different modalities were acquired in response to emotional stimulus by cleverly obtaining the synchronization between the stimulating system and data collection systems. The use of fNIRS however hampered the EEG data acquisition from frontal electrodes and also covered the eyebrows which are necessary for studying facial expressions of the subjects. The frontal electrodes such as F5, F8, AF7, AF8, AFz, Fp1, Fp2, Fpz, F7 and F6 were removed for the sake of collecting fNIRS data. The EEG and fNIRS acquisition system and fNIRS and video acquisition system used by Savran et al. are shown in Figure 1.1 and Figure 1.2

respectively. For elicitation of emotions when acquiring fNIRS, EEG and peripheral signals, images from International Affective Picture System (IAPS) (Lang et al., 2008) were shown to the subjects. The images belonging to three classes of emotions namely calm, positive exciting and negative exciting were selected on the basis of their Mean Arousal (MA) and Mean Valence (MV) values. The criterion used for selection of images is shown in the Table 1.1.

Table 1.1: Criterion of selection of emotion evocative stimuli

Class of emotion	Arousal ratings	Valence ratings	Quadrant of emotion	Number of images selected
Calm	MA<4	4<MV	HVLA	106
Positive Exciting	MA>5	MV>6.8	HVHA	71
Negative Exciting	MA>5	MV<3	LVLA	150

However for positive excited emotions, the sexually exciting images were rejected. The fNIRS+ EEG + other physiological signals were acquired (Figure 1.1) from 5 subjects in 3 sessions. All the subjects were right handed males. The EEG signals were acquired at a sampling frequency of 1024 samples per second except the subject in session 1 whose data was acquired at a sampling frequency of 256 samples per second.

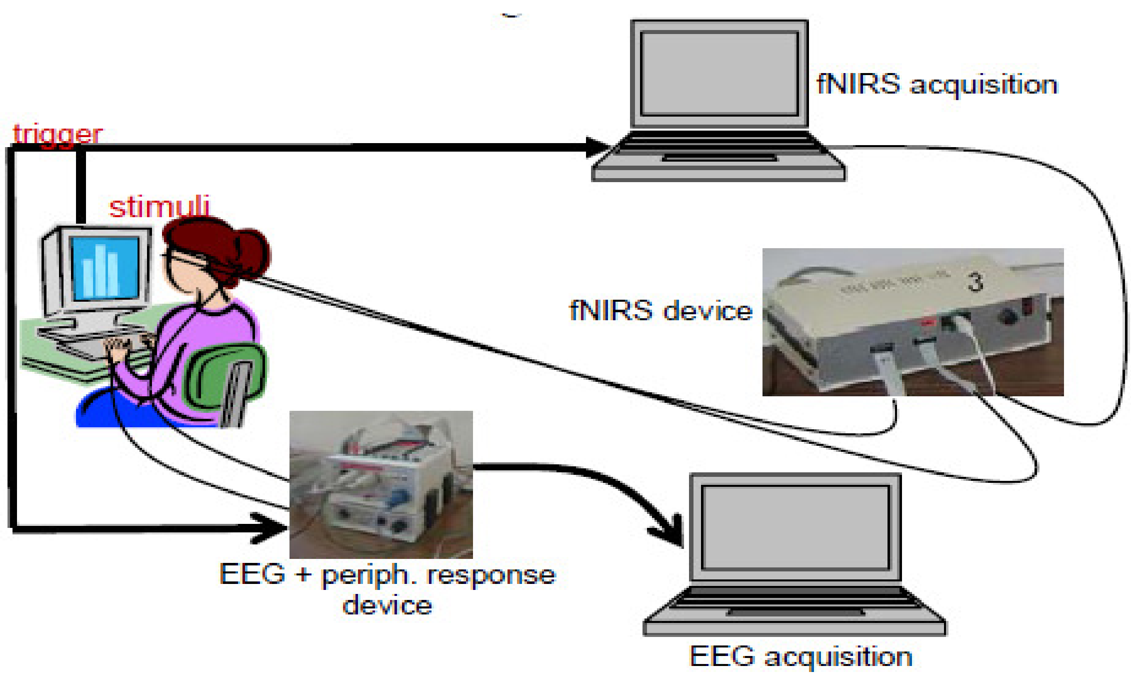


Figure 1.1: The EEG and fNIRS acquisition system (Savran et al., 2006)

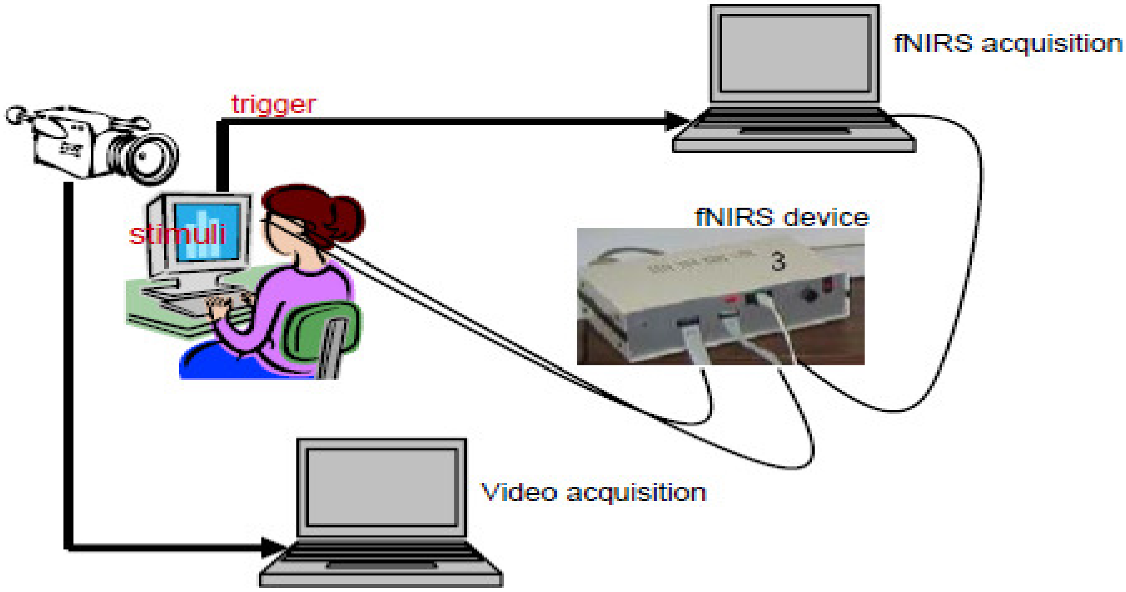


Figure 1.2: The fNIRS and video acquisition system (Savran et al., 2006)

The protocol used for presenting emotion evoking images to the subjects is shown in Figure 1.3(Savran et al., 2006).

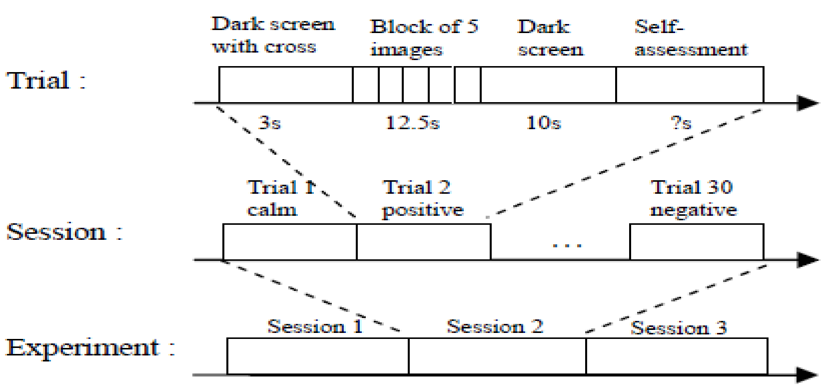


Figure 1.3: The protocol used for presenting stimulus (Savran et al., 2006)

To evoke emotions a block containing five IAPS images belonging to a particular class of emotions were shown to the subjects. Each image in a block was shown for 2.5 seconds i.e. a full block used 12.5 seconds to evoke an emotion. To validate if the desired emotion has been evoked, Self Assessment Manikin (SAM) was used to get the ratings on a scale of 1 to 5. To prepare the subjects for a trial a dark screen with a cross symbol was shown for 3 seconds. A dark screen was presented after the emotion evoking stimulus to bring the subjects to their normal condition. A total of 30 such trials spanned every session.

In a second data acquisition protocol, fNIRS and video data was acquired from 16 subjects including 10 males and 6 females. The data acquisition protocol was improved in session 2 for few subjects by adding suitable emotion evoking images (5 in number) before the video stimulus chosen from DaFEx database (Database of Kinetic Facial Expressions). The recordings have been meticulously saved with suitable filenames. We advise readers to go through the link www.enterface.net/results/ to access database and results. Though Savran et al. report that the readings from frontal electrodes were marred by interfering fNIRS LED's and the subjects did not find the exciting emotions highly evocative, but still the database contains enough multimodal information for testing emotion classification techniques. The removal of forward EEG electrodes however may impact the emotion classification results. Further, the database would have represented all the four quadrants on arousal-valence plane, had the trials also included the stimulus related to LVLA i.e. sad class of emotion.

1.4.2 DEAP Database

The Database for Emotion Analysis using Physiological Signals (DEAP) was collected by Koelstra et al. (2012) for classification of emotions using multimodal fusion of signals. The multimodal database includes video and EEG signals, physiological signals such as GSR, respiration amplitude, skin temperature, ECG, Blood Volume Pulse (BVP), ElectroOculoGram (EOG) and EMG signals. The database has been collected using videos as evocative stimulus. Since the study includes the classification results also, the database acquisition details have been explained explicitly in the review section.

1.4.3 MAHNOB HCI Database

Soleymani et al.(2012) worked to collect a multimodal signal database for classification of emotions. The signal database contains the signals from 27 participants of which 11 are males and 16 are females. The signals such as EEG, GSR, skin temperature, respiration amplitude, facial reaction of subjects (using cameras), audio signals and eye gaze data were recorded in response to emotional evocative stimulus. The acquisition of data was done in two experiments. The physiological signals including EEG were collected using Biosemi Active II system. The EEG data was collected from 32 channels placed according to 10-20 International System. In a preliminary experiment, the subjects were asked to rate the selected videos for tagging to a suitable emotional class. The video that got maximum tags was selected to induce that respective emotional feeling among the subjects. The SAM was as well used for collecting valence and arousal feelings. Twenty videos of time length 34.9 to 117 second including some old weather reports were selected to be shown to the subjects. The data was initially recorded from 30 participants (17 females and 13 males) but some discrepancy in data collection of subjects 9, 12 and 15 leaves data from 27 subjects for analysis. The I experiment included multiple choice questions for self assessment associated with emotional tagging and rating of arousal, valence, dominance and predictability on a 9 point scale where as the II experiment involved Yes/No feedback.

It is worthy to mention here that while performing emotional classification using SVM Radial Basis Function (RBF) kernel, the best classification results were obtained on the modality obtained by fusion of EEG and Gaze data. After performing cross validation, an accuracy of 67.7% was obtained while performing classification along arousal axis and 76.1% along valence axis. The use of physiological signals even did not yield the high classification results. The data available publicly has been used by various scientists and researchers working in the field of Human Computer Interface (HCI) for validation classification of emotions.

The database primarily including EEG signals obtained using emotional stimuli are discussed here. The analysis on the available databases using different processing and classification techniques yield different results and provide an opportunity to the researchers to compare, improve and most importantly validate the already existing studies. The results and conclusions can vary with variation in signal processing, feature selection and classification techniques. To avoid confusion and make the emotion classification study a practically usable application in the real time world, the validation of published results has become a need of the hour.

1.5 Literature Survey

An extensive literature survey has been carried out related to the emotion classification using EEG signals and transition of emotions among human subjects. The gist of the findings is explained here.

1.5.1 Literature Survey on EEG based Emotion Recognition

Russell (1980) in his seminal work prescribed an affective space model for illustrating a dimensional approach in which emotion was described through a two dimension space. In this early work, the opposite emotions were placed at 180^{o} to each other while the unrelated emotions were placed at 90^{o}. Starting with the state of mind 'aroused' placed at 90^{o}, the opposite state tired was placed opposite to it at 270^{o}, while pleased being unrelated to aroused state was placed at 0^{o}, while the opposite of pleased i.e. miserable was placed at 180^{o} as shown in Figure 1.4. This model was very primitive and was further refined to have two distinct orthogonal axis named as valence and arousal (Bradley and Lang 1994).

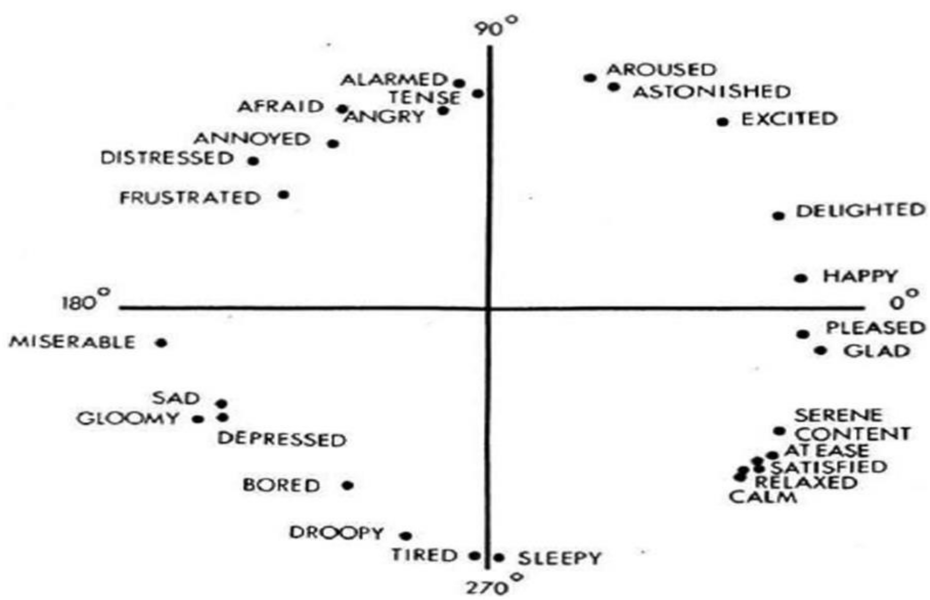


Figure 1.4: Circular scaling of 28 affect words (Russell, 1980)

Picard et al. (2001), while classifying emotions on a single subject, found that the physiological features of different emotions on the same day tend to cluster more tightly than do the features of the same emotion on different days. Chanel et al. (2005) determined arousal dimension using the fusion of EEG and physiological signals on multiple subjects. After pre-processing the signal, six features were determined by averaging the power determined from the electrodes placed at different locations in six different frequency bands. Horlings (2008) used the database of eNTERFACE 2006 collected by Savran et al. (2006) in conjunction with the self obtained EEG data using stimulus from IAPS pictures. The emotions were classified into five classes along arousal and valence axes. The signal conditioning operations were performed by using an open source toolbox called EEGLab (Delorme and Makeig, 2003). The data was re-referenced using a Current Source Density (CSD) technique for the measurement of anterior alpha asymmetry, as suggested by Hagemann et al. (2001). Horlings (2008) found that classification accuracy improved as the number of classes to be classified was reduced. For two class classification along arousal and valence using SVM, accuracy rates of 68% and 72% respectively were reported. For five class classification, the accuracy rates remained below 40%.

Frantzidis et al. (2008) provided the classification of an arousal dimension from the fusion of galvanic skin resistance and EEG signals by using pictures from the IAPS as a medium of stimuli. Frantzidis et al. (2010) classified neurophysiological data into four emotional classes, namely high valence high-arousal (HVHA), low-valence high-arousal (LVHA), high-valence low-arousal (HVLA) and low-valence low-arousal (LVLA), using average ERP and event-related oscillation features from the acquired EEG signals. For developing a subject independent emotion classifier, the average ERP features were acquired from Fz, Cz and Pz electrodes only. The emotions were classified into four classes by first classifying emotions into low arousal and high arousal classes and then used two separate classifiers to classify low arousal and high arousal data along the valence axis. Since high accuracy results (81.3%) have been reported in this study, the methodology of their data acquisition and analysis has been used in our study as well for comparison of results. However, when validating this classifier model, we found that the critical discussion of results is necessary before proposing this accuracy.

Petrantonakis and Hadjileontiadis (2010a) obtained EEG signals from three EEG channels namely Fp1 and Fp2 (in unipolar mode) and F3 and F4 (in bipolar mode) using a Mirror Neuron System (MNS) concept for emotion elicitation. In this case, the subjects were shown faces selected from Pictures of Facial Affect database (Ekman and Friesen, 1976) representing 6 states of emotion i.e. happiness, sadness, anger, fear, disgust and surprise. The data was acquired from right handed subjects involving 9 males and 7 females at a sampling frequency of 256 Hz. After performing preprocessing operations, the Higher Order Crossing (HOC) features were extracted from averaged EEG signals. The classification of emotions was done in a one versus all approach using SVM polynomial classifiers. The polynomial order was fixed at 5. Three other classifiers such as Quadratic Discriminant Analysis (QDA), k-Nearest Neighbor (k-NN) and Mahalanobis Distance (MD) classifiers were used for different combinations of electrodes and feature vectors. It is noteworthy to mention that the training data consisted of data from 5 subjects and the test data from 3 subjects. So for 16 subjects and analyzing the data on a single electrode would mean lower samples for training and testing. On combination of three channels, the best classification accuracy of 85.17% has been reported using SVM polynomial classifier. However, in a one versus all scenarios, the emotion classification results are comparable with our study. Further, as one versus all classification technique has been used, the same data will have to go through six classifiers and the output of each classifier would ultimately define the classification of a test trial. Jenke et al. (2014) validated that emotion classification results are better with HOC features, but the classification accuracies were not that high as reported by Petrantonakis and Hadjileontiadis (2010a). We have clearly described the total number of test samples for each class of emotion in our proposed study, which we found missing in Petrantonakis and Hadjileontiadis (2010a). Further, if we go by the emotional states chosen, happiness could be an emotion that may be a mixture of two or more emotions such as joy and bliss and may thus lie in first or fourth quadrant in arousal-valence plane. So we feel, an initial classification into arousal-valence plane can form basis of classification of emotions further in a particular quadrant.

Murugappan et al. (2011) classified emotions into five classes by extracting features such as Recoursing Power Efficiency (RPE), Logarithmic Recoursing Power Efficiency

(LRPE) and Absolute Logarithmic Recoursing Power Efficiency (ALRPE) by decimating EEG into different frequency bands (Singh, 2013). The features determined from EEG signals by decomposing them into different frequency bands have been used by number of researchers to classify emotions (Li and Lu, 2009; Lin et al., 2010; Nie et al., 2011; Murugappan et al., 2011; Liu and Sourina, 2013; Mühl et al., 2014; Zheng et al., 2016). Jenke et al. (2014) however found no major difference among the attributes used by Murugappan et al. (2011).

Koelstra et al. (2012) in their seminal work not only analyzed the single trial EEG signals for classification of emotions along arousal and valence axis, but as well generated a database of EEG, frontal video and other peripheral signals for classification of emotions. The database has been widely used and is highly popular among the researchers involved in the field of emotion recognition and those studying Human-Computer interaction. The database is known as "DEAP database". Apart from video and EEG signals, the database includes physiological signals such as GSR, respiration amplitude, skin temperature, ECG, BV, EOG and EMG signals. The EEG and peripheral signals were collected from 32 subjects (50% females). The EEG data was collected on 32 electrodes placed according to 10-20 International system at a sampling frequency of 512 samples per second. To elicit emotions, 40 videos of duration one minute each were selected. The selected videos had extreme arousal and valence ratings to ensure the elicitation of emotions along the four quadrants. The data was collected in two lab experiments with 20 videos shown in each experiment. The data acquisition system consisted of a display system where the emotions related to LVHA, HVHA, HVLA and LVLA were presented to the subjects using a "Neurobs Presentation System". The emotion elicitation epoch consisted of 2 second display of the trial number, a cross symbol for 5 second for baseline measurement followed by a stimulus related music video for 1 minute. The self assessment of arousal, valence, dominance, liking/disliking and familiarity was taken at the end of each trial. The physiological signals were acquired on a separate system.

While analyzing EEG signals, the authors found high correlation between valence and brain signals. It is as well prudent to mention here that the researchers found high interpersonal variability in the emotions and brain activation. Considering this, the authors recommended subject dependent emotion classification approach over subject independent emotion classification approach. The analysis of single trial EEG signals, peripheral physiological signals and videos was done to classify emotions along arousal domain (Low Arousal and High Arousal) valence domain (Low Valence and High Valence) and low liking/high liking of the presented stimulus. A Gaussian naive Bayes classifier was used for classification of emotions. The attributes such as power spectral (logarithm) in different frequency bands namely theta (4-8Hz), slow alpha (8-10 Hz), alpha (8-12 Hz), beta (12-30 Hz), gamma (< 30 Hz) as well as difference in spectral power obtained from symmetrical electrodes placed in the left and right hemisphere were acquired. Various features (106) such as average, average of derivative, power in different frequency bands etc. were acquired from other physiological signals. A total of 53 audio features were as well extracted. From the classification results, it was found that arousal was better classified with EEG features, valence with peripheral and like/dislike with video features. It was easier to classify valence as compared to arousal. The fusion of modalities showed good classification results for valence (64.8%) as compared to arousal (61.6%) and liking (61.8%). Only with EEG features, the arousal was classified with an average accuracy of 62%, valence with 57.6% and liking with 55.4% accuracy. The correlation between the features, EEG electrodes and arousal/valence emotion revealed that for arousal classification CP6, Cz, FC2 electrodes could be used and Oz, CP1, T7, C4, FC6, PO4, Cz, CP6, CP2, T8 and F8 were better related with the classification of valence emotion. In this seminal work, the authors did not present the best classification accuracies obtained for individual subjects. We in our study have tried to present the best as well as average emotion classification accuracies. Also both single trials and average EEGs have been analyzed to obtain both subject dependent and subject independent classifiers.

Koelstra and Patras (2013) performed affective tagging of multimedia by using a multimodal approach. The fusion (both feature level and classifier level) of facial expressions and EEG signals acquired from 24 subjects were analyzed not only for recognition of emotion in the arousal - valence space but as well for affective tagging of videos. For emotion classification, the EEG signals and video data acquired in MAHNOB HCI interface (Soleymani et al., 2012) were used. The MAHNOB HCI dataset acquired from 27 subjects consists of various physiological signals such as EEG, ECG, respiration amplitude, skin temperature and video data acquired from 6 cameras along with eye gaze tracker output. Please see https://mahnob-db.eu/hci-tagging/ for further information. The EEG data was acquired on 32 channels placed according to 10-20 International System. For elicitation of emotions, Hollywood videos of different lengths (35-117 second) acquired from different sources such as youtube.com and blip.tv were used. The authors worked on the data set of 24 subjects. For video data analysis, the data from frontal camera was used. The EEG data was down sampled to 128 Hz and to remove artifacts, band pass filtering (4-45Hz) was performed. The power spectral features in five different frequency bands (Koelstra et al., 2012) were used as attributes for classification of emotions. Different electrodes such as CP6, Cz, FC2 (for arousal) Oz, CP1, T7, C4, FC6, PO4, Cz, CP6, CP2, T8 and F8 (for valence) were used for extraction of features. The authors added Fp1 and Fp2 electrodes in the described set of electrodes for classification of arousal, valence and control. The difference in power spectral features from 9 left-right hemisphere electrodes was used. From the video data (frontal camera), action units activations were detected in first step as per the previous study (Koelstra et al., 2010a). The meta-features extracted from this system were then used for classification of arousal, valence and control. Recursive Feature Elimination (RFE) technique and Independent Component Analysis (ICA) technique was used for feature selection. For two class classification, Gaussian Naïve Bayes (GNB) classifier (Please see http://scikit-learn.sourceforge.net/ for more information related to classifier and Bayesian Ridge Regression technique) was used on individual as well as data set obtained by fusion of two modalities i.e. EEG and face attributes. The fusion at feature level and decision level is shown in Figure 1.5. The average classification results obtained for the two feature selection techniques on individual and fusion of modalities are shown in Table 1.2

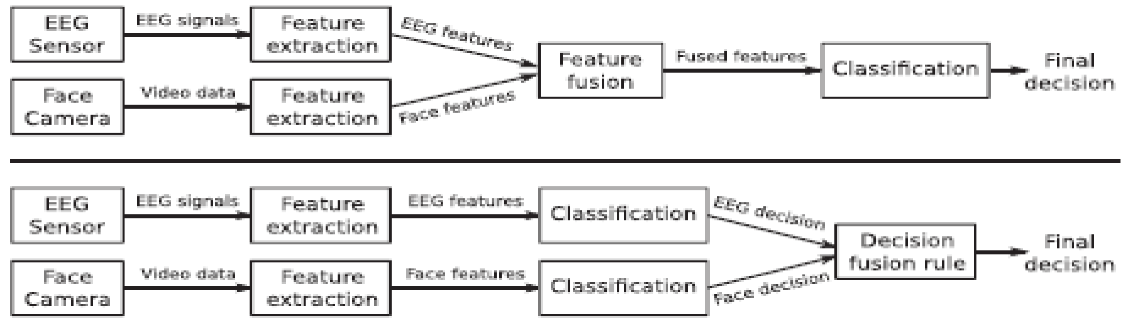


Figure 1.5: Fusion at feature level and decision level (Koelstra and Patras, 2013)

Table 1.2: Results on different modalities using ICA and RFE feature selection techniques

	Modality	Average binary classification results (%)		
		Arousal	Valence	Control
ICA	EEG	66.0	71.5	67.5
	Face	65.0	64.5	64.5
	Fusion	68.0	72.5	67.5
RFE	EEG	67.5	70.0	63.5
	Face	67.5	64	62.0
	Fusion	68.5	73	68.5

The results show that the EEG attributes gave better emotion classification results as compared to the face attributes for both feature selection techniques. Also the fusion of attributes improved results but the addition of face attributes resulted in inaccuracy. At the same time it is prudent to mention that the frontal-central region electrodes were found more suitable for classification of arousal, valence and control domains. Analyzing decision level fusion, EEG attributes were as well found to be more suitable for classification as compared to face attributes. However, some of the conclusions related to this study were countered by Soleymani et al. (2015). Further, the fusion at classifier level improved accuracy as best classification accuracy of 72.5 % has been reported for arousal, 74% for valence and 73% for control. The results obtained when using ICA do not differ considerably from those obtained using RFE technique. The results with RFE feature selection technique are marginally better.

Jenke et al. (2014) tested features collected as per the 33 previous studies on EEG based emotion recognition and found that the features such as HOC (Petrantonakis and Hadjileontiadis, 2010a), Fractal dimension (Sourina and Liu, 2011) and Hjorth parameters and features obtained from frequency bands β and γ (Liu and Sourina, 2013) gave better emotion classification accuracies. The EEG data was collected from 16 subjects including seven females and nine males at a sampling frequency of 512Hz. The emotions belonging to five classes namely happy, curious, angry, sad and quiet were evoked using IAPS images. A total of 160 images (32 images belonging to each class) were shown to the subjects. Various feature extraction techniques were employed to reduce the feature set. The best of results were reported when using Min-Redundancy-Max-Relevance (mRMR) technique. Considering that the ERP extraction requires averaging of multiple number of EEG signals, the ERP feature was not considered in this subject dependent study. The studies based on using ERP for emotion classification are a few. The studies on single trial ERP analysis and real time emotion recognition system are even rarer.

Liu et al. (2014) used kernel Fisher discriminate analysis for selecting features among the extracted power spectrum features in different frequency bands. The EEG signals were collected from 62 EEG channels at a sampling frequency of 500Hz. The IAPS images belonging to four classes LVHA, HVHA, HVLA and LVLA (25 each) were used for eliciting emotions. The feature extraction methods involved Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), kernel PCA and kernel FDA also called kernel Fisher's emotion pattern (KFEP). The classification was compared using k-NN classifiers, SVM, imbalanced SVM (I-SVM) and IQK-SVM classifiers. The subject wise evaluation showed arousal and valence classification remained low even after using various feature extraction techniques such as PCA and LDA. The use of PCA for feature reduction is effectively described by Joshi et al. (2013) while analyzing speech signals. Using k-NN classifier, best subject wise accuracies were reported for KFEP method of feature extraction. The valence classification accuracy lied between 78 - 82% for 10 subjects with KFEP and k-NN classification technique. Similarly, high results were reported for arousal classification (just above 70% to 90%) using KFEP feature extraction technique. The average arousal accuracy of 82% and average valence accuracy of 79.5% was reported when using k-NN classifier with KFEP feature extraction process. The best average arousal accuracy of 84.8% and best average valence accuracy of 82.7% had been reported using IQK-SVM when using features generated through KFEP.

Soleymani et al. (2015) found that classifying emotions on the basis of attributes determined from facial expressions produced higher accuracy results as compared to classification of emotions based on EEG attributes. These results are in contrast to the study of Koelstra et al. (2013) which showed better emotion classification results with EEG as compared to facial expressions. Another important observation by Soleymani et al. was that the facial expressions on account of the emotional stimulus affect the emotional sensitive features of EEG. The data used for emotional analysis is a subset of MAHNOB HCI interface data (Soleymani et al., 2012). The stimulus contained short videos up to the length of 117s collected from different sources such as movies, YouTube, weather reports etc. The detailed information is available at https://mahnob-db.eu/hci-tagging/. However in brief, a 32 electrode Biosemi Active II EEG system was used to capture EEG signals at a sampling frequency of 256Hz. The re-referencing to average reference was done. Also another modality i.e. the facial expressions from a frontal camera were analyzed for emotion classification.

The attributes such as log of power spectral density features from different frequency bands such as theta (4Hz-8Hz), alpha (8Hz-12Hz), beta (12Hz-30Hz) and gamma (more than 30Hz) determined from all 32 EEG electrodes were used as features for emotion classification. For facial expressions, the distance of eyebrows, lips and nose from the reference point (obtained after averaging of inner corner of eyes and nose landmarks) were used as attributes. A strong correlation was found between the features obtained from facial expressions and the features from EEG used in detection of valence. For testing the attributes (single as well as fusion at both attribute level and decision level) various testing techniques were used. The subject dependent emotion classification was done using Long Short Term Memory Recurrent Neural Network (LSTM-RNN), Multi Linear Regression (MLR), Support Vector Regression (SVR) and Continuous Conditional Random Field Models (CCRF). The emotion classification results showcasing Average Pearson Correlation Coefficient (APCC) and Root Mean Square

Errors (RMSE) obtained for different modalities viz; EEG, Face, fusion at feature level and fusion at decision level are shown in Table 1.3.

Table 1.3: Results on different modalities using different classification techniques

Model	MLR		SVR		CCRF		LSTM-RNN	
Metric	APCC	RMSE	APCC	RMSE	APCC	RMSE	APCC	RMSE
EEG	0.22±0.36	0.055±0.030	0.21±0.35	0.060±0.027	0.26±0.49	0.048±0.035	0.24±0.34	0.053±0.029
Face	0.38±0.35	0.049±0.026	0.38±0.36	0.051±0.025	0.44±0.41	0.053±0.027	0.48±0.37	0.043±0.026
FLF	0.38±0.34	0.049±0.025	0.33±0.33	0.055±0.024	0.44±0.40	0.53±0.028	0.40±0.33	0.047±0.025
DLF	0.38±0.37	0.047±0.028	0.36±0.37	0.050±0.026	0.42±0.46	0.050±0.029	0.45±0.35	0.044±0.026

The Table 1.3 shows the best classification results for LSTM-RNN type of classification technique on the modality involving attributes obtained from the face expressions as compared to Koelstra and Patras (2013) where the classification results with feature level fusion were the best as shown in Table 1.2. Both the studies are based on MAHNOB HCI data. Further Soleymani et al. (2015) show the lowest accuracy results with EEG as compared to Koelstra and Patras (2013) where the valence classification was found to be more precise with EEG. It could be attributed due to different selection of electrodes, different feature reduction techniques and different pattern classification techniques. Even the facial expression results obtained in a study by Soleymani et al. (2012) and Soleymani et al. (2015) are not similar. Anyhow all three studies show how important it is to validate the results on emotion classification and the results and predictions can vary with electrode selection, feature selection and pattern classification techniques. Soleymani et al. (2015) also stressed on the need of analyzing EMG output for studying emotions to correlate the findings with those obtained using facial expressions. Koelstra and Patras (2013) added Fp1 and Fp2 electrodes in the already determined best suitable set of electrodes. Similarly, it would have been interesting to see the correlation between the informative features from Fp1 and Fp2 EEG electrodes with attributes from facial expressions. We determined the effect of including Fp1 and Fp2 in the set of selected electrodes when classifying emotions along arousal and valence domains.

Lin and Jung (2017) improved the classification accuracies along arousal and valence axis by using conditional transfer learning approach for the subjects who could not be evoked emotionally to the right extent under laboratory conditions. The EEG data was collected from 26 subjects by using music as an intervention to evoke emotions corresponding to four classes of emotions namely LVHA, HVHA, HVLA and LVLA. After decomposing the signals into different frequency bands such as δ, θ, α, β and γ, the differential laterality features were acquired. The ReliefF method was used for feature reduction. The use of Transfer Learning approach improved the results but the average classification accuracy along arousal and valence remained lower than 65%. It is worth mentioning that Jenke et al. (2014) found mRMR technique better over ReliefF feature selection technique.

Menezes et al. (2017) acquired features as used in Jenke et al. (2014) and Petrantonakis and Hadjileontiadis (2010a) to classify emotions along arousal and valence. The EEG collected in DEAP database was used. The statistical, spectral power (after decomposing EEG into α, β, δ, and θ bands) and HOC features collected from four frontal electrodes Fp1, Fp2, F3 and F4 were used for classification of emotions. The classification of emotions was carried out using tripartition as well as bipartition of arousal and valence scale i.e. the classification of emotions was done into three and two classes along both arousal and valence axis. The SVM as well as Random Forest Classifiers were used for classification. No averaging of EEG signals before feature extraction has been reported. The information related to classification process i.e. classification is one versus all or simultaneous classification has been carried out is also missing. In general, the classification methodology explaining the subject dependent classification needs to be elaborated further. However, Menezes et al. found statistical features better suited for classification of emotions especially arousal unlike HOC features found by Jenke et al. (2014). Using Random Forest classifier, the best classification accuracy was obtained for statistical features obtained from different bandwaves. For three classes, accuracy of 63.1% along arousal and 58.8% along valence where as for two classes, 74% for arousal and 88.4% for valence was reported. It must be noted that the lowest accuracies were reported for HOC features. Similarly, using SVM classifiers generated classification accuracy of 59.7% and 55.1% for three state classifications along arousal and valence respectively. The two class classification results were a bit better with arousal classification accuracy of 57.2% and valence classification accuracy of 83.2%. The results are different from the studies of Petranokis and Hadjileontiadis (2010a), Koelstra and Patras (2013) and Soleymani et al. (2015).

For classification of emotions, studies based on average and single trial ERP are limited. Nicolaou et al. (2008) successfully analyzed single trial ERPs for BCI by applying ICA technique. Zhang et al. (2013) found evidence that average amplitude differences can be attributed to the variations in single trial amplitudes (P1, N170, VPP, N3 and P3) between experimental conditions. Zhu et al. (2015) used rapid serial visual presentation paradigm to elicit emotions and analyzed variation in ERP amplitudes (P2 and late positive potential) corresponding to three emotional states along the valence axis (neutral, positive and negative). The P2 amplitude varied in response to emotional stimuli as compared to non emotional stimuli. The rapid serial visual presentation system has been successfully used to analyze single trial ERP and latency features for emotional related research (Jung et al., 2001; Limpiti et al., 2010; Luo et al.; 2010; Blankertz et al., 2011; Zhang et al., 2013; Yi et al., 2015). Leyh et al. (2016) determined the variation in ERP specifically P3 amplitudes on subjects with different attachment levels. The subjects performed an oddball experiment with IAPS images belonging to negative, positive and neutral contexts running in the background. The attenuation in P3 amplitudes was noticed on subjects with insecure-dismissing attachment. Also, the authors calculated lower hit rates for subjects with insecure-dismissing attachment under low valence emotional stimuli as compared to other category of subjects. Van Dongen et al. (2016) related the attenuation in LPP (late positive potential) amplitudes in EEG in response to the low valence and high valence IAPS pictures when presented in art form as compared to the presentation of images as pictures. Importantly, it was found that emotional assessment of visual stimuli happened quickly causing changes in EEG. The LPPs were found to be symmetrically distributed over the scalp with maximum amplitude found at midline electrodes.

The ERP features have been used by some other researchers for analysis. (Cuthbert et al., 1995; Cuthbert et al., 2000; Delplanque et al., 2004; Delplanque et al., 2005; Luck 2005; Sivaradje et al. 2005; Conroy and Polich, 2007; Quiroga et al., 2007; Nicolaou et al., 2008; Li et al., 2014; Wu et al., 2014; Hidalgo-Muonoz et al., 2013; Izurieta Hidalgo et al., 2015). The studies on real time emotion classification are limited**.** Cowie et al. (2000) developed an instrument 'FeelTrace' to detect the type of emotional stimuli. The observers recorded the perceived emotion on a circular evaluation space.

Attempts have as well been made by the researchers to develop real time emotion classifiers. Debener et al. (2012) developed a low cost wireless (Alibakshi-Kenari et al., 2016) EEG for field recordings and used single trial P300 to classify indoor and outdoor recordings. Ko et al. (2015) used wireless EEG for fatigue detection. Prashanth and Kumar (2014) used a GPRS based system for real time health monitoring. The wireless mobile EEG systems without memory limitations (Please see http://pressrelease.brainproducts.com/liveamp/ for more details) and supporting mobile computing features are being designed and tested (Agrawal et al., 2017). Jatupaiboon et al. (2013) made an attempt to design a real time EEG based happiness detection system. The EEG signals were acquired from 14 electrodes at a sampling frequency of 128 Hz from 10 subjects including 9 females and one male. For elicitation of happy and unhappy emotions, 50 low valence and 50 high valence pictures from Geneva Affective Picture Database (GAPED) (Dan-Glauser and Scherer, 2011) were selected. The classical music was as well used. Jatupaiboon et al. decimated 5s EEG signals into five 1s EEG signals. The Wavelet Transform was then applied to decompose EEG signals into five frequency bands. The power spectrum density feature was determined from frequency bands and then normalization of the features was done to classify happy and unhappy emotions of the subjects. The subject dependent and subject independent classification has been performed by using Gaussian SVM with Leave-One-Trail-Out Cross-Validation (LOTO-CV) and Leave-One-Subject-Out Cross-Validation (LOSO-CV) techniques respectively. The average accuracy of classification was 65.12% for subject independent classification and 75.62% for subject dependent classification incase three older subjects were removed. Further, for some subjects, the classification accuracy was lower than 55% when default 2-class classification accuracy is 50%. It is worth mentioning that the authors had performed the baseline removal operation in addition to normalization operation on the acquired EEG signals. This would definitely add to the lag in real time operations using EEG. An overview of emotion classification studies is shown in Table 1.4

Table 1.4: Review of emotion classification techniques based on EEG signals

S.No	Reference, Stimulus, Number of subjects	Number of classes	Physiological signals	Classifier	Features	Results
1	Chanel et al. (2005), IAPS, 4	2[Calm and Exciting]	EEG	FDA	Power and statistical features	55%
			Physiological signals such as GSR, Plethysmograph, Respiration and Temperature			53%
			Fusion of signals			54%
		2 [Calm and Exciting]	EEG, Physiological signals and fusion of the two.	NB		50-54%
2	Horlings (2008), IAPS, eNTERFACE 2006 data and 10 other subjects	5 along valence and arousal axis	EEG	SVM	ERD/ERS, cross correlation, peak frequency and Hjorth parameters	31% along Valence 32% along Arousal
				ANN		31% along Valence 28% along Arousal
				NB		29% along Valence 35% along Arousal
		3		SVM		37% along Valence 49% along Arousal
		2				72% along Valence 68% along Arousal
3	Frantzidis. et al. (2008), IAPS,26	4[Joy, Fear Happiness and Melancholy]	EEG and GSR	ANN	ERP features and the GSR duration	80%, 100%, 80%, 70%
4	Moradi and Khalili (2009), IAPS, eNTERFACE 2006 data	3[Calm, Negatively excited and Positively excited]	EEG	QDC	Statistical features and power in 10 frequency bands ranging from .25 Hz to 2.75 Hz	63.33% - 66.66%
			Peripheral signals such as GSR, Temperature, B.P. and Respiration			55% - 51.66%
			EEG+Peripheral (without correlation dimension)			61.8% - 62.2%
			EEG (combination with correlation dimension)			66.66%- 76.66%
5	Frantzidis et al.(2010), IAPS, 28	4[HVHA, LVHA, HVLA, LVLA]	EEG	MD	ERP and Event related oscillation	79.46%
				SVM		81.25%
6	Petrantonakis and Hadjileontiadis (2010 a), PFA database	6 [happy, sad, anger, fear, disgust and surprise]	EEG	SVM polynomial QDA, k-NN, MD	HOC	85.17% using SVM on attributes of all 3 channels. (Best average accuracy)

S.No	Reference, Stimulus, Number of subjects	Number of classes	Physiological signals	Classifier	Features	Results
7	Murugappan et al.(2011), Visual and Audio stimuli	5[Happy, Fear, Neutral, Surprise and Disgust]	EEG	KNN	Entropy and Power Ratios	70-93%
				LDA		68-92%
8	Koelstra et al. (2012), Music Videos, 32	2 along Arousal [Low Arousal/ High Arousal], 2 along Valence [Low Valence/High Valence], [Low Liking/ High Liking]	EEG	GNB	Spectral Power features from EEG	Arousal-62% Valence-57.6% Liking-55.4%
			Peripheral Signals such as EMG, GSR, Temperature, BVP and Respiration, EOG and ECG		statistical features such as average, average of derivative, band energy ratio and standard deviation etc	Arousal-57% Valence-62.7% Liking-59.1%
			MCA		(MFCC, pitch, and zero crossing rate	Arousal-65.1% Valence-61.8% Liking-67.7%
			Fusion		Fusion all three	Arousal-61.6%, Valence 64.7% Liking 61.8%
9	Soleymani et al.(2012), Hollywood Videos, 27	3 along Arousal[Calm, Medium Arousal and Excited/Activated], 3 along Valence [Unpleasant, Neutral Valence and Pleasant]	EEG	SVM RBF Kernel	Spectral features from different frequency bands	Arousal-52.4%, Valence-57%
			Peripheral Signals such as ECG, GSR, respiration amplitude, and skin temperature		HRV, standard deviation of beat interval change per respiratory cycle, average skin resistance , band energy ratio, mean of derivative, range, spectral power in bands etc.	Arousal-46.2% Valence-45.5%
			Eye Gaze		Features from pupil diameter, gaze distance, eye blinking and gaze coordinates such as average, standard deviation, spectral power in different bands, skewness, blink depth approach time ratio etc.	Arousal-63.5%, Valence-68.8%
			Fusion		Fusion EEG and Gaze	Arousal-67.7%, Valence-76.1%

S.No	Reference, Stimulus, Number of subjects	Number of classes	Physiological signals	Classifier	Features	Results
10	Jatupaiboon et al. (2013), GAPED pictures and classical music, 10	2[Happy and Unhappy]	EEG		PSD	Subject independent – 63.67%, Subject dependent-70.55% (average accuracies)
11	Hidalgo-Muñoz et al. (2013), IAPS, 26	2[LVHA and HVHA]	EEG	SVM	Power	96.2-100% (Best with RFE)
12	Koelstra and Patras (2013), MAHNOB HCI database, 24	2 along Arousal [Low Arousal/ High Arousal], 2 along Valence [Low Valence/High Valence], [Low Control/ High Control]	EEG	GNB	Power spectrum density features	With ICA:- Arousal- 66%, Valence-71.5%, Control-67.5%
						With RFE:- Arousal-67.5%, Valence-70%, Control-63.5%
			Facial Expression Features		Action units activations	With ICA:- Arousal- 65%, Valence-64.5%, Control-64.5%
						With RFE:- Arousal-67.5%, Valence-64%, Control-62%
			Fusion of modalities and fusion at decision level		Fusion	Arousal-72.5% Valence-74% Control-73% (Best Results)
13	Jenke et al. (2014), IAPS, 16	5 [Happy, Curious, Angry, Sad and Quiet]	EEG	QDA with diagonal covariance estimates	Time domain features such as power, mean, S.D., HOC, Hjorth Features, NSI, FD. Frequency domain features such as Band power, Entropy and Power ratios etc.	32 - 43%, (Average of 5 feature selection techniques)
14	Liu et al. (2014) IAPS, images,10	2 [Low Arousal/ High Arousal and Low Valence/ High Valence]	EEG	(IQK-SVM), ISVM, kNN, SVM	PSD with feature reduction techniques PCA, LDA, KFDA(KFEP) Kernel PCA	Arousal-84.8%, Valence-82.7% (Best average accuracies using IQK-SVM)

S.No	Reference, Stimulus, Number of subjects	Number of classes	Physiological signals	Classifier	Features	Results
15	Soleymani et al.(2015), MAHNOB HCI database, 28	Valence	EEG	LSTM-RNN, MLR, SVR and CCRF	Power spectrum density features	Best APCC - 0.45 on LSTM-RNN with decision level fusion
			Facial Expression Features		distance of eyebrows, lips and nose	
			Fusion of modalities and fusion at decision level		Fusion	
16	Lin and Jung (2017), music videos, 26	2 [Low Arousal/ High Arousal and Low Valence/ High Valence]	EEG	GNB	DLAT (Spectral power)	Without TL Arousal- 35.1 to 78.7%, Valence-21.8 to 85.4% With TL Arousal-64%, Valence-64% (Average results)
17	Menezes et al.(2017), DEAP database	2 [Low Arousal/ High Arousal and Low Valence/ High Valence]	EEG	RF, SVM	Statistical parameters, Spectral band power and HOC	3 classes using RF Arousal-63.1%, Valence-58.8%, 2 classes using RF Arousal-74%, Valence-88.4% 3 classes using SVM Arousal-59.7%, Valence-55.1%, 2 classes using SVM Arousal-57.2%, Valence-83.2%

FDA, Fisher Discriminant Analysis; NB, Naïve Bayes classifier; QDC, Quadratic Discriminant Classifier, GNB, Gaussian Naïve Bayes Classifier, GSR, galvanic skin resistance; BVP, blood volume pressure; EMG, electromyogram; BP, blood pressure; SVM, support vector machine; ANN, artificialneural network; MD, Mahalanobis Distance; KNN, k-nearest neighbours; ERD, event-related desynchronization; ERS, event-related synchronization; LDA, linear discriminant analysis; LSTM-RNN, Long Short Term Memory Recurrent Neural Network; MLR, Multi Linear Regression; SVR, Support Vector Regression; CCRF, Continuous Conditional Random Field Models; APCC, Average Pearson Correlation Coefficient APCC; ICA, Independent Component Analysis; RFE, Recursive Feature Extraction; IQK-SVM, Imbalanced quasiconformal kernel SVM; PFA, Pictures of Facial Affect database; HOC, Higher order crossing; NSI, Non –Stationary Index; FD, Fractal Dimension; DLAT, Differential Laterality; GNB, Gaussian Naïve Bayes; RF, Random Forest; MFCC, Mel-Frequency Cepstral Coefficients; MCA, Multimedia Content Analysis

1.5.2 Literature Review on Emotion Transition

Aftanas and Golosheikin (2003) described the changes in EEG attributes obtained from Experienced Meditators (EM) and Novice (non-experienced) Meditators (NM). To bring the change in state of consciousness Sahaja yoga meditation technique has been used. The EEG signals in the frequency range of 0.5 to 50Hz have been recorded under three stages of meditation. The first stage is the subject's entering into meditation; the second when the subject is under deep meditation also known as the state of consciousness with inhibited mental activity and the third is when the subjects exited from the state of meditation. On the conclusion of the experiment the subjects rated three types of activities on a 0 to 9 point scale.

1) Their mental activity under meditation.
2) The level of positive emotional experience of happiness (bliss, satisfaction) during meditation
3) The level of anxiety (worry, dissatisfaction) when undergoing through meditation (because of instability in meditation) or the impossibility of attaining the meditation state.

The physiological analysis has been done by analyzing power spectrum in different frequency bands. The decimation of EEG signals into δ, θ and α frequency bands have been performed using the techniques proposed by Doppelmayr (1998a) and Doppelmayr (1998b). The results show EMs exhibit better psycho-emotional stability and capacity for identifying emotions as compared to NMs. The difference in EEGs and cortical activity during meditation, confirms the generation of positive emotional experiences in EM. The authors claimed that the EM exhibit better ability to identify emotions but it is as well prudent to mention that the feedback of subjects was taken for only calm state. However, the research shows the variations and changes of power in different frequency bands for Mediators.

Xiang et al. (2005) described a mental state model to predict the next state of emotion. The probability of transition among seven emotion states namely Happy, Sad, Anger, Disgust, Fear, Surprise and Serene was determined on the basis of a Mental Transition State Network (Figure 1.6) based on a psychological questionnaire.

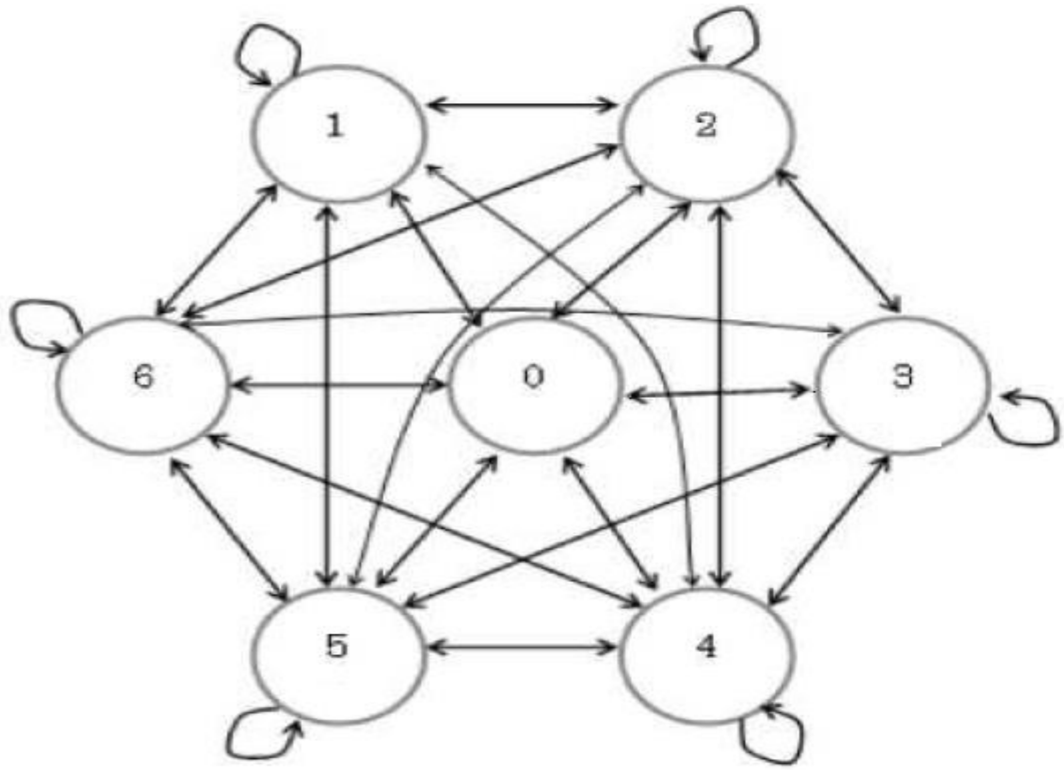


Figure 1.6: Mental state transition network for 7 emotion states (Xiang et al., 2005; Ren, 2009)

In Figure 1.6, 0 refers to emotional state Serene, 1 is Happy, 2 is Sad, 3 is Angry, 4 means Disgust, 5 means Fear and 6 refers to emotional state Surprise.

The psychological questionnaire was posed to subjects from both Japan and China. Interestingly in the questionnaire the subjects were asked to consider themselves in one state of emotion and predict the possibility of transition to another emotion in the absence of any external or internal stimuli. Human mental states show transition from one state to another on a certain condition. The methodology used for collecting data was asking the participants to imagine a certain emotional situation, and select the possibility on a 0-10 scale of what the next emotional state will be. It was found that in the absence of a stimulus the subjects in the study perceived to stay in the quadrant (if we divide the seven emotions into four quadrants defined by arousal and valence axis) in the absence of a stimulus and interestingly the data collected apparently shows this holds good for low valence high arousal (LVHA) and high valence low arousal (HVLA) emotions. Further from the results shared by the authors it could be concluded that the probability of transition of emotions from LVHA state to LVLA or vice versa were higher where as the probability of transition from angry to happy emotion is lower. The probability of transition among different emotion states were determined using statistical methods. The researchers concluded that

1) Most likely no transition of emotional state occurs in the absence of any stimulus.

2) The "Surprise" state gives distinctive results as compared to other emotional states.

3) The transition probability among the opposite emotional states is the lowest.

4) A tendency to transition into the calm state is the maximum in the absence of external stimulus.

As per the questionnaire format it seems that the subjects were not informed about classification of emotions before collecting data. How can the subjects be considered to experience full blown emotion in the absence of external stimulus. It is obvious that the transition to neutral state will occur in the absence of external stimulus. A small briefing about the representation of emotions in four quadrants would have been more helpful to the respondents. Further, it is prudent to mention that in the mental state transition network (see Figure 1.6), the authors considered serene as an emotion among the selected seven emotions, but in statistical analysis describing probability of transition among the seven states, serene is not included but has been replaced by an emotional state “quiet”.

In a seminal work, Ren (2009) proposed a simulation model for predicting and creating emotions. To enhance the research, the analysis of voice, visual image and the speech patterns have been carried out to study the course of transition of emotions. For recognition of emotions, a MSTN was proposed which consisted of various modules such as Human Emotion Recognition Engine (HMRE) for processing of emotional information present in speech patterns, sound patterns and visual patterns and the Machine Emotion

Creation Engine (MECE) to generate synthetic emotions which is as well based on speech, voice and gestures. The method used for recognizing and generating emotions is shown in Figure 1.7.

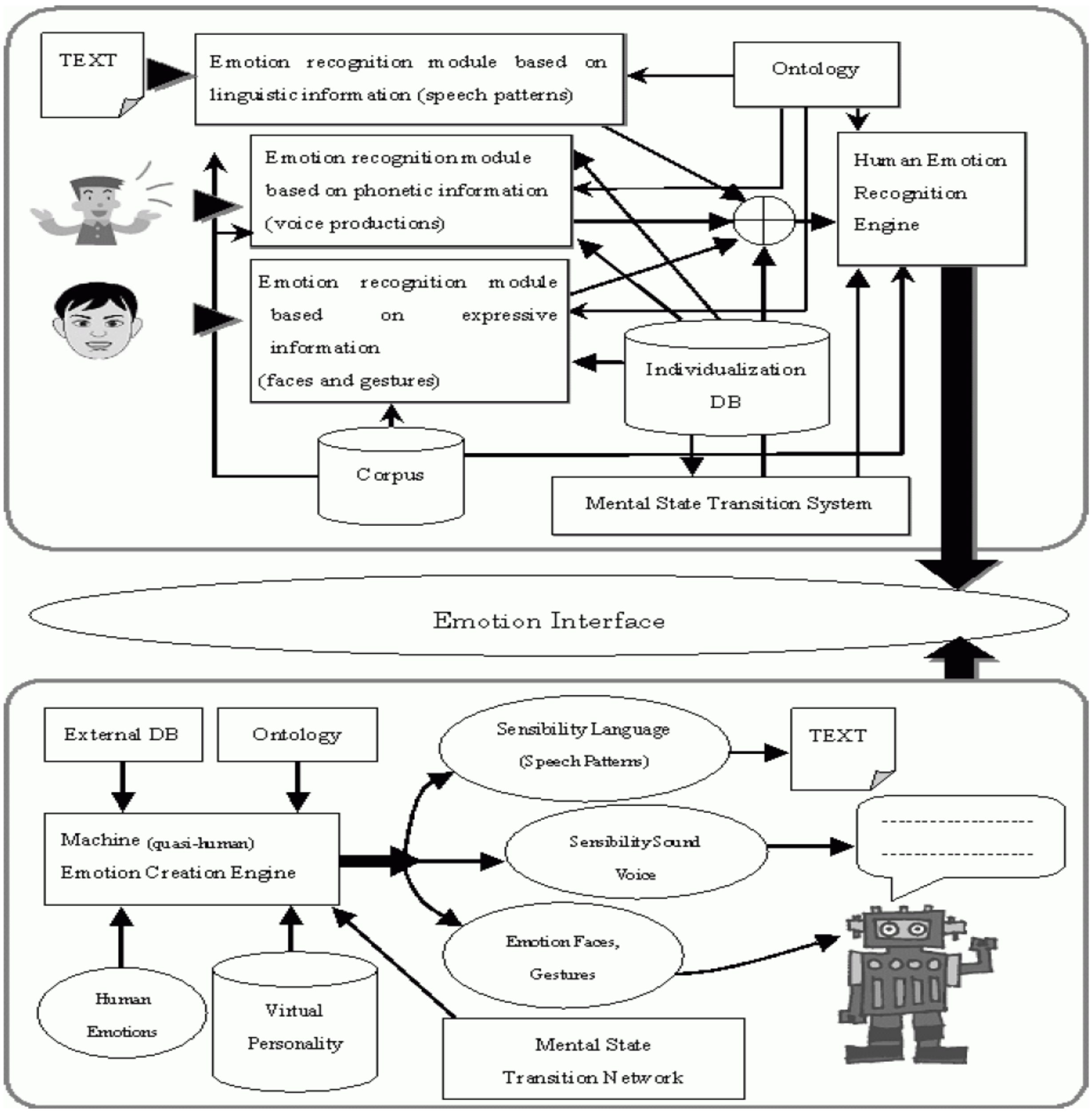


Figure 1.7: HMRE and MSTN (Ren, 2009)

The MSTN developed to determine the likelihood of transition of human emotions in the absence of external stimulus is shown in Figure 1.6. The network has been obtained by using a questionnaire method which is well explained by Xiang et al. (2005). The pattern of transition of emotions is similar to the one proposed by Xiang et al. (2005). The prediction of human emotion based on facial expressions was done using Facial Action Coding System (FACS) (Please see a study by Ekman and Friesen (1978) on Facial action coding system: a technique for the measurement of facial movement for details). As far as emotion quantification from speech pattern is concerned, an emotional dictionary and different databases were developed. Though a well apt system for human emotion recognition is given, but the MSTN used in the system does not consider the transition of emotions for evocative stimuli. The results related to emotion transition lacks the results determined using physiological signals.

Han et al. (2010) studied the circumstantial based musical intervention to impel transition of moods of human subjects. To know the degree of transition of emotions, Emotion State Transition Matrix was developed. The authors contended that emotion state at any time depended upon different emotions. Considering the Component Process Theory (Scherer, 2005), each emotion state was described by number of adjectives. So the emotion state vector was like $Es(t)=\{ es_1(t), es_2(t), \ldots\ldots, es_n(t)\}$ where $Es(t)$ is an emotion state at instant 't' described by emotional strengths '$es_1(t), es_2(t), \ldots\ldots, es_n(t)$' of different emotions. The Emotion Transition Matrix was calculated by determining $Es(t_{final}) - Es(t_{init})$. The effect of intervention on emotion transition could be determined by analyzing the value of $es_1(t_{final}) - es_1(t_{init})$. The positive value suggested that the intervention caused a transition of emotion where as a negative value suggested an inverse effect of transition. A zero value suggested that the intervention did not cause any effect on the emotion state. It is prudent to mention here that the researchers inter mixed mood and emotions number of times in their research. An example cited by them relates more with stress (work related) rather than short and intense feeling at that instant of time. Further the researchers used a web based questionnaire to collect data about user's emotional state. The recommendation of an intervention was decided by using SVM classifiers. It is as well important to mention that no physiological data was collected and analyzed for validating the emotion transition effect.

Pao et al. (2010) used speech signals collected by lu (2004) to analyze the different emotions present in a speech signal. The analysis performed on speech signals using different segmentation techniques such as uniform, end point, and whole segmentation techniques yielded an average accuracy of 73% using weighted discrete-KNN classifier. It is noteworthy to state that the authors did not identify the elements necessary to bring the transition of emotions among the subjects. It can be concluded that the authors concentrated more on emotion classification from speech rather than analyzing emotion transition.

Filipowicz (2011) discussed the effect of transition of emotion states on the interpersonal (social) interactions and relational impressions. The authors performed three experiments where the outcomes of transition of emotion states from happy to angry, angry to happy and steady state emotional states (steady-state anger and steady-state happiness) have been compared. In this study, 187 undergraduate students of University of Pennsylvania participated. The authors found that transition of emotion from happiness to anger leads to better results in negotiation outcomes and better relational impression among the negotiators than when the negotiator displayed steady state anger. It could also be concluded that angry to happy emotional transition as compared with steady-state happiness is insignificantly related to differences in negotiation outcomes but significantly related to differences in relational impressions. Since the transition of emotions effect the interpersonal negotiations and relations, it becomes necessary to corroborate the transition of emotions with physiological signals.

To study if the meditation process causes changes in EEG signals of the subjects, Goshvarpour and Goshvarpour (2012) performed experiment on 25 healthy women subjects. The EEG was collected from three central electrodes (Fz, Cz and Pz) within a frequency range of 0.1 to 50 Hz. The EEG data was collected before and during the process of meditation. The master helped some of the subjects in meditation. The features such as Wavelet coefficients and correlation coefficients were extracted from the obtained EEG. These two different type of features were separately used as inputs to test four different classifiers. The classifiers that were used are Fisher classifier, Quadratic classifier, k-NN and Parzen classifiers. The accuracy obtained using Wavelet coefficients with Fisher classifier was 85.02%, Quadratic classifier was 82.55%, k-NN 81.06% and Parzen was 84.75% where as the classification accuracy on Correlation dimension for the above mentioned classifiers was 92.37%, 90.27%, 89.29% and 92.37% respectively. The results show the variation in state of mind before and during meditation. The effect of meditation, i.e. after the meditation data too needs to be extracted and analyzed to see the changes in state of mind before and after the meditation on subjects. Our study analyzes the EEG data before and after the meditation process. Taking a clue from this study, we have used a master who helps the subjects under observation in meditation. The wavelet transform technique had also been used by Saxena et al. (2002) for analyzing ECG signals.

Ichimura and Mera (2013) described how MSTN can help predict the responses to an emotional stimulus. The authors tested the stepwise operation of a MSTN. The developed network predicted an emotion by first representing the input utterance of a subject into a case frame (Fillmore, 1968) i.e. obtaining the predicate, subject, object, aspect and tense etc. from the sentence. Then the Favorite Value related to the object (in the range of -1 to 1) present in the sentence was determined. The number of objects which could be used was limited in this study. The FV value was determined using a questionnaire. The pleasantness and unpleasantness component of emotions were determined using Emotional generating calculations (EGC). Please see "Knowledge Based Intelligent Information and Engineering Systems, 7th edition, Springer, pp 425-429" by Vasile Palade et al. for more details. The pleasant/unpleasant types of emotions were then classified into different emotions. The MSTN was used to calculate the transition cost (probability) associated with transition of emotion from current state to next state. Interestingly even with intervention the transition cost related to transition from angry to happy state of mind was low (0.143). In this study as well no physiological signals were collected to validate the results. This shows a strong intervention is required to bring the subjects from angry state of emotion to happy state of emotion. Using only a statement (from a story) to evoke emotions also limits the stimulating effect on subjects.

The study of Filipowicz (2011) outlined the effects of transition of emotions in negotiations, a study by Van Kleef (2014) outlined how and when the symmetric and asymmetric effects are produced due to exhibition of emotions in an organization. By symmetric effects the author means that the outcome is positive for the exhibitor when a positive emotion is expressed and the outcome is negative for the expresser when a negative expression is displayed. imilarly the asymmetric effects indicate advantageous outcomes for the expresser when a negative emotion is displayed and disadvantageous outcome when a positive expression is displayed. Further the authors in their elaborative review pointed out the studies of Lelieveld et al. (2012) that how a display of discontentment can produce positive effect on concessions whereas the display of guilt can result in exploitation (Van Kleef et al., 2006). Of course, the effect depends on the perceiving ability of others and the situation in which an exhibitor of the emotion is. The transition of emotions does produce asymmetric effects but at the same time the effects of emotions other than happy and anger need to be thoroughly reviewed.

Xiaolan et al. (2015) quantified the perception of subjects related to their current emotional state (reappraisal parameter) in a range of -10 to +10 to observe how the initial emotional state, current emotion evoking stimulus and individual personality characteristics of a subject affects the regulation and transition of emotions. The emotion regulation has been described as per Gross's process model of emotion regulation (Gross 1998a; Gross 1998b). The emotional affect on a subject can be experiential, behavioral and physiological. The authors finely concluded the effect of reappraisal parameter on the probability of occurrence of emotions. Incase if the reappraisal parameter is zero, the occurrence of an emotion solely depended on the emotional stimulus but the increase in reappraisal parameter increased the probability of occurrence of positive emotions while decreasing the probability of occurrence of negative emotions. Though the results defined are significant but the validation from physiological data is missing.

Kato and Hagiwara (2016) used an effect of internal and external stimulus to study the transition of emotions. The inference regarding the transition of emotions has been made using Fuzzy logic. The effect of external input and internal emotional state on emotion transition has been measured using a modeling equation 1.1

$$In(n)=p\, In(n-1)+Tr(n) \qquad 1.1$$

where In(n) is the current emotional state, n is the time step, Tr(n) is an emotion transition value and p is a forgetting coefficient.

To apply fuzzy rules efficiently, the value of current emotional state has been normalized to stay within the range {0,1}. The experimentation has been performed by using 25 sentences from a famous Japanese story "Urashimo Taro" on 13 subjects. The subjects were asked to imagine the degree and charge related to each sentence. The analysis was confined to four states of emotion namely Joy, Sadness, Fun and Anger. The initial internal state of emotion was assumed to be zero. The experiment was performed for all 25 statements. The correlation between the output of the model and the perception of subjects was more than 0.7. Though high correlation between the results of the model and the response of the subjects was obtained, no physiological parameters were obtained to validate the result. Further, it can be seen that the subjects were not able to differentiate more between the Sad and Angry state of emotion as is evident from their response to the statement "Children catching Turtle and bullying it". It would have been more interesting to see the transition from Angry to Joy state of emotion but the authors have not explained the transition of emotions in this manner. The sequence in which the emotional sentences were shown to the subjects is as well not known.

Almost all the studies on emotion transition reviewed here are based only on the self assessment of subjects and none have corroborated their findings by acquiring and analyzing EEG or other physiological signals before and after the transition of emotions. In this study, apart from developing an emotion classifier, the testing of an intervention technique has been performed by acquiring EEG before and after the intervention.

1.6 Research gaps

The researchers have contributed a lot in classification of emotion states but the validation of classification techniques for the subjects under study still needs to be taken up. Jenke et al. (2014) validated emotion classification results of previous research studies using different features but left the validation of emotion classification using ERP features. It is pertinent to mention here that most of the emotion classification studies are based on power spectrum density features or statistical features acquired from single trial or average EEG signals but the studies based solely on average ERP for emotion classification are limited. The use of single trial ERP features for emotion classification is even rarer. Also the studies employing single trial EEG features for emotion classification are mostly subject dependent. The online emotion classification using single trial EEG signals is limited by the baseline and noise interference effects. The use of difference of ERPs can be helpful as far as baseline variations and noise interference effects are concerned. The employability of difference of ERP features over single trial ERP features for online and subject independent classification of emotions needs to be tried and tested. The ERP studies so far have not been on frontal electrodes only, central electrodes only or parietal electrodes only but all have evaluated and classified the emotions using a group of electrodes. Most of the researchers have not included Fp1 or Fp2 electrodes of EEG for emotion classification. Some studies do mention improved classification on account of the use of Fp1 and Fp2. This needs to be validated. In a prominent study on average ERP attributes, high arousal and valence classification accuracies have been obtained at the expense of orthogonal nature of arousal and valence domains. Further, the results need to be presented in an unambiguous manner by clearly specifying the trials correctly classified and how inaccuracy of one classifier adds into the total error count, resulting in a lower overall accuracy. Apart from these main shortcomings, the optimal selection of electrodes for recognition of emotions needs to be explored further. For acquisition of physiological signals time locked with emotion evocative stimulus, low cost synchronization techniques need to be developed and tested.

As far as the emotion transition is concerned, though meditation techniques have been used to experiment over the subjects but none specifically concentrates on bringing the subjects from low valence high arousal (LVHA) state to high valence low arousal state (HVLA). The meditation techniques reportedly cause the changes in physiological variables and EEG but the tasks that can cause the transition of human emotion states have not been tested through self assessment and using EEG based emotion classifier. The mental state transition networks (MSTN) proposed so far have either been theoretical or based on individual feedback. Validation using the data acquired before and after the meditation is missing.

1.7 Objectives of Research Work

- To acquire EEG data, preprocess the signal and extract emotionally sensitive features for classification.
- To identify, validate and/or develop the four-state EEG signals based classifier for human emotions.
- To identify the position of electrodes which are sensitive to emotional changes.
- To arrive at the set of recommendations to bring the subjects from low valence high arousal state (LVHA) to high valence low arousal state (HVLA).

1.8 Proposed Methodology

Our quality of life is more dependent on our emotions than on physical comforts alone. This is motivation enough to classify emotions. The classification of emotions along any of the domains viz; arousal, valence and dominance is possible by utilizing the orthogonal nature of emotions. To evoke emotions the visuals from IAPS shall be used. The acquisition of ERP features require projection of emotion evoking stimulus on one computer system while simultaneously putting a mark on the second computer system acquiring EEG. A low cost synchronization technique using two keyboards with galvanically connected key is proposed to be used to synchronize EEG signals with emotion evoking stimulus. Emotion has four basic classes viz; LVHA, HVHA, HVLA, and LVLA. For each class it is proposed that an IAPS picture belonging to that class be shown to the subject for 1 second followed by a black screen for subsequent 1.5 second, thus totaling to 2.5 second for an epoch. Simultaneously, EEG from all the electrodes namely Fp1, Fp2, F3, F4, F8, Fz, Cz, Pz, P3 and P4 be acquired through proper marker indicating the start of an epoch. IAPS pictures are pre classified as LVHA, HVHA, HVLA and LVLA images. A set of pictures taking one from each category is created and shown in 2.5 x 4= 10 second. Forty such sets are shown in continuity, in 400 second. To rule out any exceptional case where the emotion evoked in the subject may not be in agreement with the pre classified IAPS picture, we propose to use SAM after the data acquisition. Relevant ERP parameters like P100, N100, P200, N200, P300 and N300 along with the latencies at which they occur are then obtained for each electrode. These features are proposed to be used for classification of emotions either in absolute or differential mode. The classifier used is proposed to be SVM whose polynomial order needs to be optimized experimentally. It is further proposed to develop a suitable intervention to bring the subjects from LVHA to HVLA category. Further the subjects in HVLA category can be crosschecked for this emotional state through self assessment and the developed classifier, thus validating the proposed classifier. Overall work flow for developing the emotion classifier is shown in Figure 1.8, while the validation of classifier is depicted in Figure 1.9.

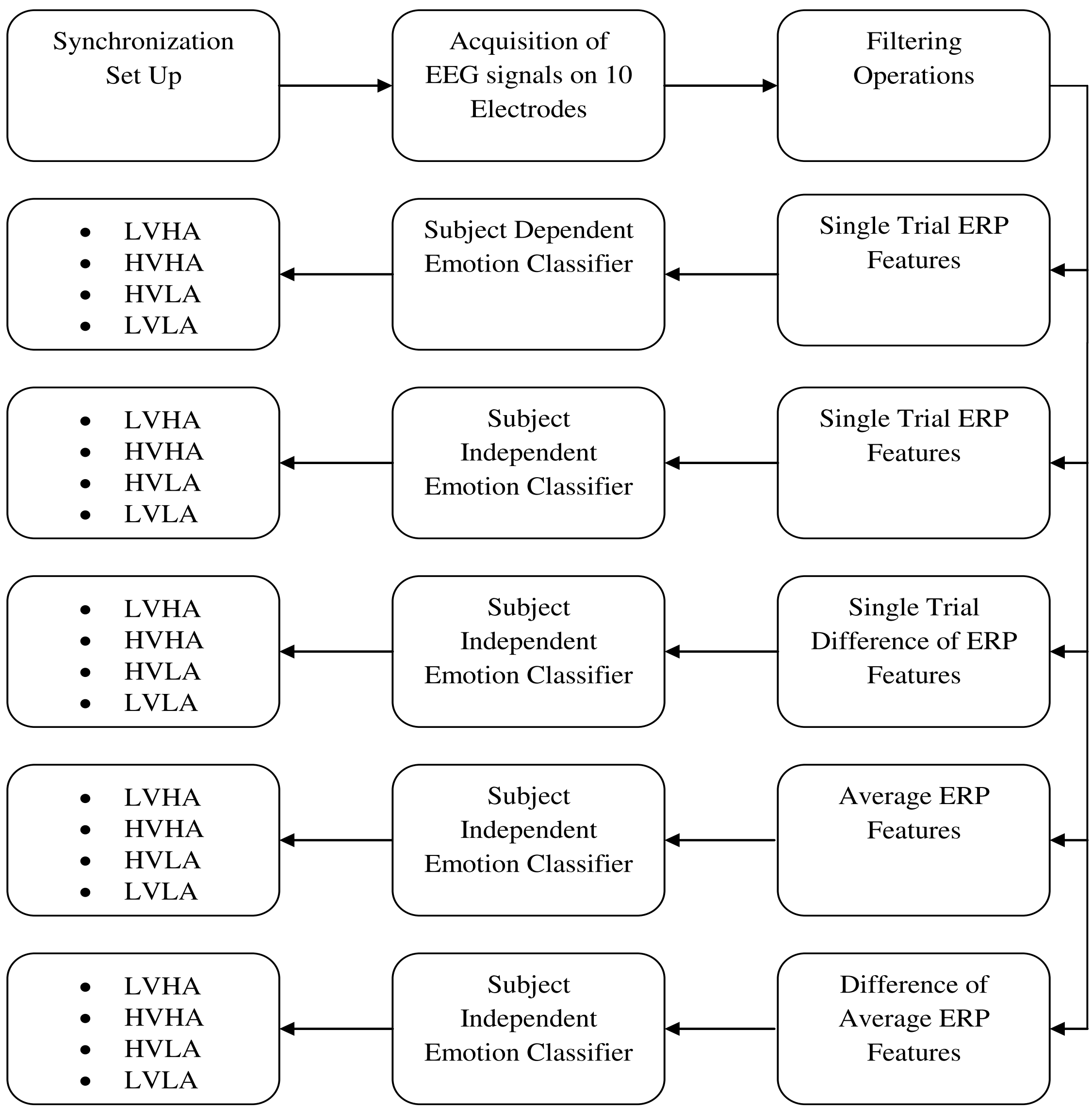


Figure 1.8: Development of EEG based emotion classifier

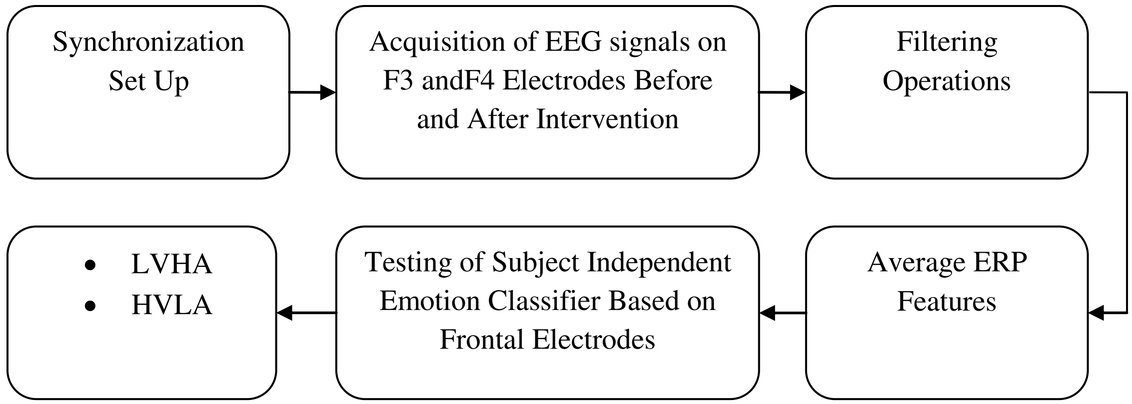


Figure 1.9: Validation of EEG based emotion classifier

1.9 Organization of Thesis

- **Chapter1** in this study presents the necessity of studying emotions along with the existing relevant work in the field of emotion recognition and transition of emotions. The research gaps and objectives to be achieved are listed at the end of Chapter 1.

- The first objective is to acquire EEG signals for emotion recognition. **Chapter 2** contains complete description of data acquisition protocol, selection of stimulus, type of subjects, hardware used and development and testing of low cost synchronization technique to acquire time locked EEG signals. The classification of emotions requires selection of attributes from acquired EEG signals. Whereas the review in Chapter 1 dictates the selection of event related potential (ERP) attributes, Chapter 2 lists the ERP and latency features acquired from EEG signals after performing preprocessing operations on the acquired EEG signals.

- The second objective is to identify, develop or validate a four state emotion classifier. **Chapter 3** explicitly portrays the development of subject dependent emotion classifier using single trial ERP features, subject independent emotion classifier using single trial ERP features, subject independent emotion classifier using difference of single trial ERP features, subject independent emotion classifier using average ERP features and subject independent emotion classifier using difference of average ERP features on three central electrodes namely Fz, Cz and Pz. Chapter 3 not only validates the study using ERP features but also compares the results with existing studies.

- The third objective is to identify the position of electrodes which are sensitive to emotional changes. **Chapter 4** demonstrates the four class emotion classification results obtained on different combinations of EEG electrodes viz; all EEG electrodes, frontal EEG electrodes, parietal EEG electrodes and electrodes except central electrodes to select the best combination of EEG electrodes for emotion classification. In this chapter the subject independent emotion classifiers based on average ERP features and difference of average ERP features have been developed and analyzed. Comparison with other existing studies has also been performed.

- The last objective is to arrive at the set of recommendations to bring the subjects from low valence high arousal state (LVHA) to high valence low arousal state (HVLA). The acquisition protocol, features extracted from EEG signals, the effect of intervention technique used for bringing the subjects from LVHA state of emotion to HVLA state of emotion and the validation of EEG based emotion classifier developed in Chapter 4 has been described in **Chapter 5**.

- **Chapter 6** contains conclusion and future scope of the study undertaken.

CHAPTER-2

DATA ACQUISITION METHODOLOGY

2.1 Introduction

The classification of emotions requires acquisition of peripheral signals, brain signals and facial expressions time locked with emotional stimuli. The Table 1.4 reviews how type of emotional stimulus used for evoking emotions under laboratory conditions, types of preprocessing including filtering techniques, features extracted from acquired signals and the classification techniques for classification of emotions vary. The classification of emotions is however done in arousal valence space as suggested by Russell (1980) in Circumplex Model of Affect (Figure 1.4). The techniques such as thinking about some personal happening during acquisition of data (Clynes, 1977), pictures from available data sets such IAPS (Lang et al., 2008), acoustic stimuli from database such as International Affective Digital Sounds (IADS) (Bradley and Lang, 2007), videos from youtube.com, blip.tv, Hollywood movies and DaFEx database (Battocchi et al., 2005) etc. are being used for evoking emotions. The physiological signals acquired (multimodal or single) need to be precisely synchronized with evocative stimulus to draw the correlations between the attributes and class of emotions. The synchronization techniques depend on the type of hardware and software used for acquisition of signals. It also depends on whether the physiological signals are acquired using one computer system while the evocative stimulus is run on the second computer system. In such cases, the type of software used for presentation of stimulus is important as it should be able to generate a mark/event on the first computer system apart from generating a log file related to the change in stimulus. It should be precisely able to generate a record explicitly exhibiting the time for which each stimulus (trial) was run on the first computer used for presenting stimulus to a subject. With the event mark(s) available on the data acquisition file corresponding to each change or start of stimulus, the correlation or analysis of physiological data corresponding to each emotional stimulus (trial) in an experiment can be done. For example, we are using a Biopac provided MP150 acquisition system for acquiring EEG signals in our lab and the label mark on the acquired EEG data for every change in emotional stimulus is obtained by using an STP100C module that connects the MP150 system to a stimulus presentation system. However, this is possible when all the signals are acquired using one acquisition software. For multimodal acquisition i.e. when the acquisition software is different for different physiological signals and the number of computer systems required for data acquisition is more than one then to place a mark on different acquisition computer systems simultaneously by using hardware modules such as STP100C becomes difficult. In such cases, the synchronization in time clocks of two computer systems used for data acquisition is obtained and the marks placed on one computer system are then transferred to the second computer system by reading the time instant at which event was marked on the first data acquisition system and the log file generated on the stimulus presentation system. The eNTERFACE 06 data (Savran et al., 2006) was somewhat synchronized in this manner. Taking a clue from this study and the study done by Portelli and Nasuto (2008), we developed and experimented with our own synchronization system.

2.2 Experimental Setup

One of the research objectives of our study is to acquire EEG signals corresponding to four classes of emotion. The images from IAPS have been used for evocating emotions under laboratory conditions. As can be seen from Table 1.4, Frantzidis et al. (2010) achieved the best four class classification accuracy using ERPs as attributes. Moreover, the methodology used has not been validated by any researcher to the best of our knowledge. The emotion evocation method, the attribute selection method and emotion classification technique is in fact influenced by the study of Frantzidis et al. (2010). The experimentation we performed is totally noninvasive and has the approval from University Ethics Committee. The EEG signals have been acquired using MP150 data acquisition system provided by Biopac. The EEG cap EEG100C consists of 20 Ag/AgCl electrodes placed according to 10-20 International System. The students from Thapar University above the age of 18 years volunteered to be our subjects. The data has been acquired in two experiments. In the first experiment EEG data has been acquired by evoking emotions corresponding to four classes of emotions. The second experiment involves acquisition and analysis of EEG signals related to the try out we conducted to bring the subjects from LVHA state to HVLA state.

2.2.1 Selection of Stimulus for Evoking Emotions

In this proposed study, the EEG signals have been acquired from 10 electrodes namely Fz, Cz, Pz, Fp1, Fp2, F3, F4, P3, P4 and F8 in unipolar mode. The reference electrode has been fitted on the left mastoid. The IAPS visuals used for evoking emotions belonging to four quadrants of emotions namely Low Valence High Arousal (LVHA), High Valence High Arousal (HVHA), High Valence Low Arousal (HVLA) and Low Valence Low Arousal (LVLA) (Figure 2.1) have been selected on the basis of their mean arousal and mean valence values. The methodology used for selecting images belonging to four classes of emotions is shown below in Table 2.1.

Table 2.1: The criterion used for selecting IAPS images

Class of Emotion	Mean Arousal (MA) Ratings	Mean Valence (MV) Ratings	Quadrant of Emotion on Arousal Valence plane	Number of Images Selected
HVHA	MA > 6	MV > 6	I	40
LVHA	MA > 6	MV < 4	II	40
LVLA	MA < 4	MA < 4	III	40
HVLA	MA < 4	MV > 6	IV	40

In other words, selected HVHA images are those images where mean valence >6 and mean arousal >6, HVLA images are those images where mean valence >6 and mean arousal <4, LVHA images are those images where mean valence <4 and mean arousal >6 and LVLA images were those images where mean valence <4 and mean arousal <4. To evoke each type of selected emotion, 40 images have been shown to every subject. In other words the process of evoking four emotions included 160 trials with 40 trials belonging to each class of emotion. Some of the images had to be repeated. An epoch of 2.5 second has been selected to validate the study of Frantzidis et al. (2010). Each trial included an emotion evocative stimulus of 1second followed by a cross symbol for 1.5 second. The IAPS like images used in our study and placed in suitable quadrants along the arousal and valence plane are shown in Figure 2.1.

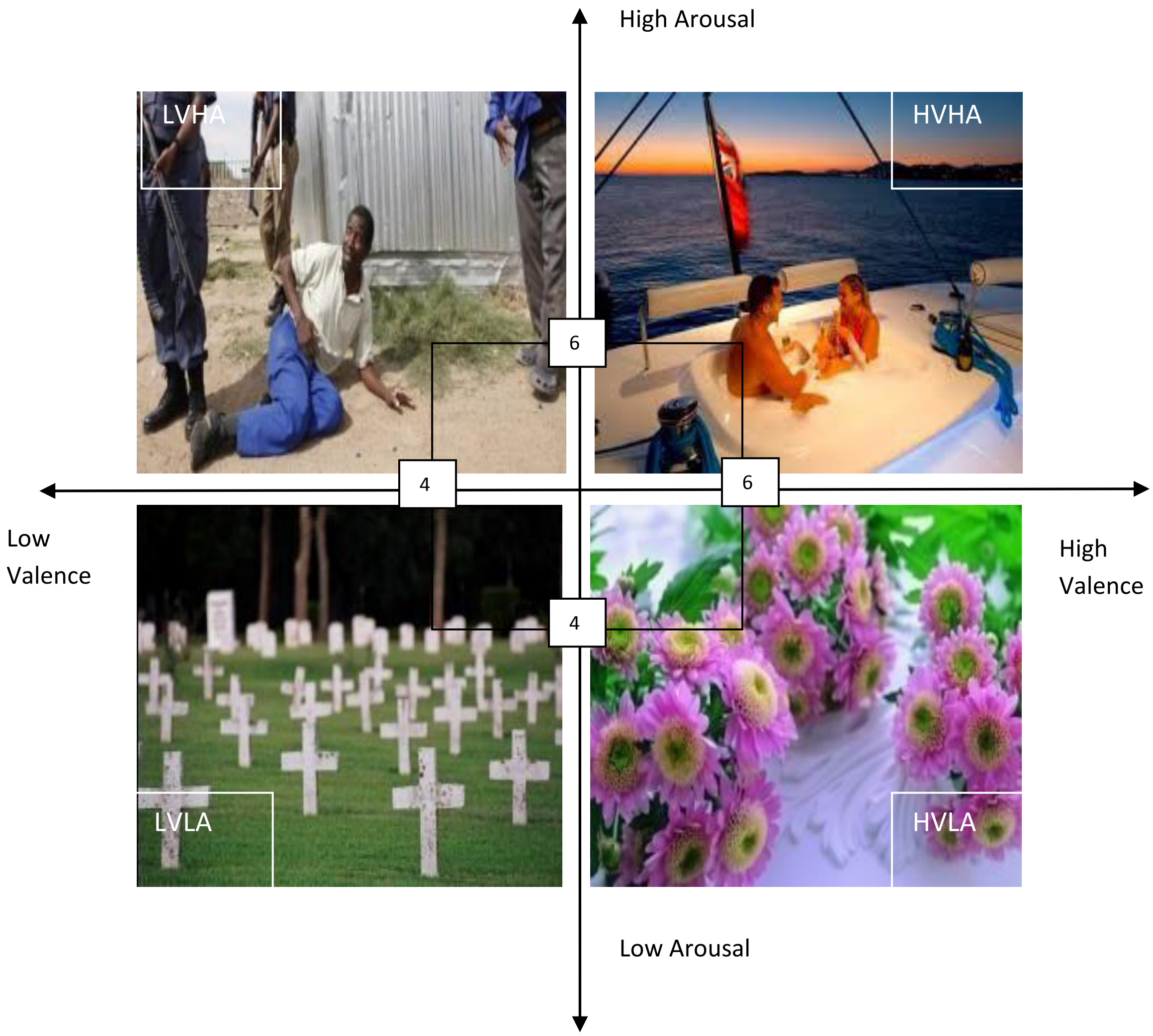


Figure 2.1: The IAPS like images used in our experiment

Though the mean arousal and mean valence ratings along with variance are specified in the image set but still to check the effectiveness of stimuli set in evoking emotions among the Indian subjects, we chose to obtain arousal and valence ratings from the subjects using Self Assessment Manikins (SAM) on a 1 to 9 point scale. Before starting with an experiment, an effort was made to transfer the information related to the quantization of emotions on arousal valence plane. To apprise the subjects of arousal valence plane and emotional quadrants such as HVHA, LVHA, LVLA and HVLA, we used a slide showing circumplex model of affect proposed by Russell (1980) in conjunction with Figure 2.2.

The subjects were well apprised that valence represents a charge of the emotion which could be positive or negative. The arousal domain represents the level of excitement.

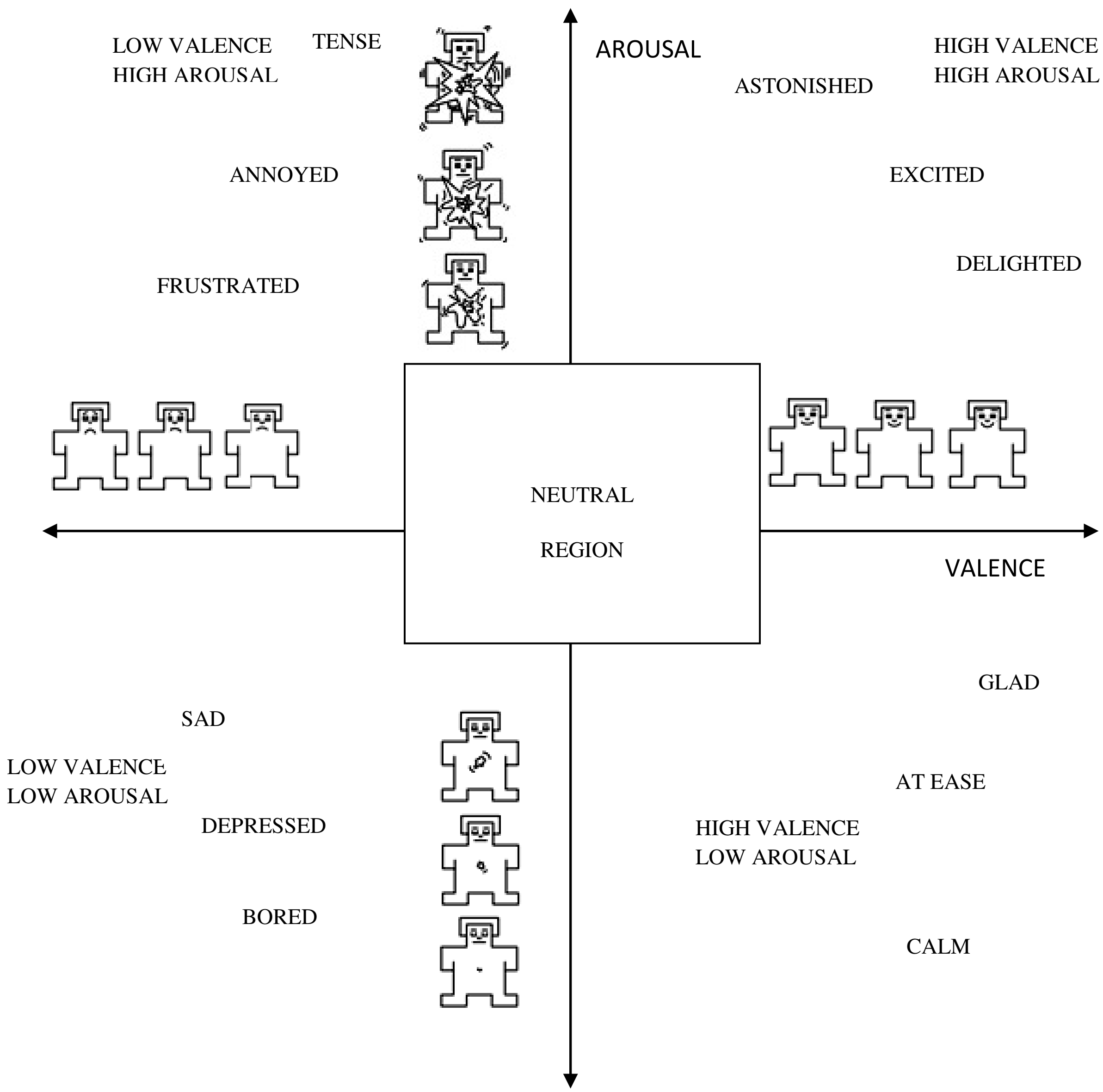


Figure 2.2: Demonstration of four classes of emotion on arousal-valence plane

Though on describing the quadrants of emotions on arousal-valence axis, it became easier for the subjects to perceive what type of emotion has been evoked with the visual stimuli, but still to make the things more convenient for them we used some adjectives and represented them on arousal valence plane just like Russells (1980). Before start of an experiment we presented the subjects with IAPS like images and evaluated how they identified their evoked emotion in terms of quadrants and adjectives. The subjects were made aware of the neutral region as well. The assessment was taken by using manikins for arousal and valence as shown in Figure 2.3 and Figure 2.4 respectively.

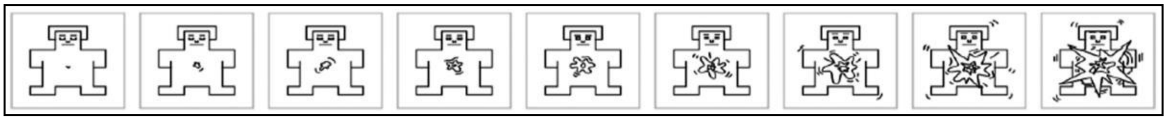


Figure 2.3: Manikins for arousal assessment

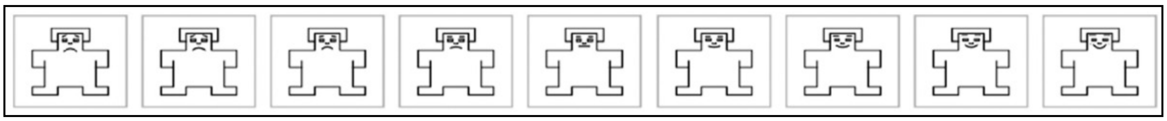


Figure 2.4: Manikins for valence assessment

The plot of actual ratings from IAPS and average assessed ratings along arousal and valence axis on a scale of 1 to 9 is shown in Figure 2.5.

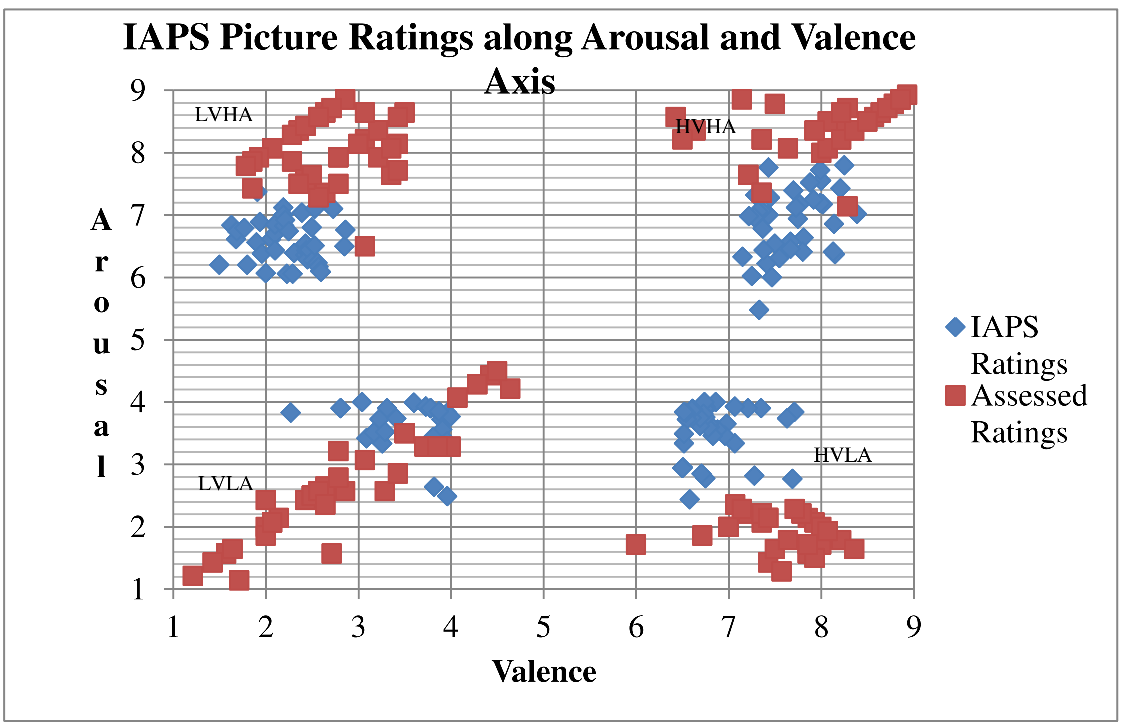


Figure 2.5: IAPS and assessed mean ratings on arousal and valence scale

The method of using Figure 2.1 (IAPS like images) and Figure 2.2 (demonstration of four classes of emotion on arousal- valence plane) to acquaint subjects with types of emotions we wish to evoke turned out to be fruitful as good ratings have been obtained for images related to LVHA, HVHA and HVLA emotions. The subjects notified that few LVLA images were not able to generate the requisite arousal level. Thus the subjects rated them in the neutral zone. To be specific certain images such as ‘‘Homeless Man’’, ‘‘Empty Pool’’, ‘‘Dishes’’ and ‘‘Finger Print’’ were rated neutral (arousal and valence ratings between 4 and 6). The subjects also rated images of ‘‘KKK rally’’ and ‘‘Cow’’ in neutral zone with mean arousal and valence ratings just above 4. Apart from the above mentioned pictures, some pictures originally rated as low valence and high arousal were rated with low valence and low arousal ratings by few subjects affecting the mean arousal and mean valence ratings. The correlation index remains above 0.83 for both arousal and valence ratings.

The process of acquisition was started after apprising the subjects about the source of images, the type of images as we did not reject arousal type (above 18 years) images in HVHA category, the acquisition protocol and the type of emotions we wish to evoke for classification. The subjects signed an undertaking in this regard that they understand the procedure of EEG data acquisition which of course is totally non invasive and they are voluntarily appearing for data acquisition. They also understood that some of the images are above 18 years category. We also acknowledged that their names would not be disclosed after experimentation.

To acquire EEG signals time locked with stimulus presentation, we developed and tested our own synchronization setup.

2.3 Development and Implementation of Low Cost Event Marker for Data Acquisition

In this study ERPs between latencies 80-120ms, 180-220ms and 280-320ms were acquired just after the presentation of stimulus. To acquire similar features from EEG, a synchronized setup is needed i.e. the acquisition computer and 4the stimulus presentation system should be time locked. For presentation of stimulus, a Neurobs Presentation platform (Version 18.0, Neurobehavioral Systems, Inc., Berkeley, CA, www.neurobs.com) was used. The Neurobs Presentation is capable of presenting stimulating images and videos with high degree of precision and generates a log file with four significant figures after the decimal place. The presentation system can place the marks on the data acquisition system exactly at the time when a stimulus changes but that requires external hardware module.

In our experiments we are using Biopac provided MP150 system along with EEG100C cap. The cap contains 20 EEG electrodes including ground for data acquisition. The data can be acquired in an Acq (Acq Knowledge Document) by using acquisition software like ACQ4.1 or ACQ4.2 etc. We used Acq 4.2 for acquiring physiological signals in our experiments. The experiments have been conducted to extract ERP attributes at different latencies from EEG signals. To acquire time locked EEG signals in Acq format with stimulus presented on a separate computer system, the STP 100C module is required which adds to the cost of equipment by at least $3000. We are claiming the cost on the basis of quotations we obtained at the time of purchasing equipments. However the studies by Savran et al. (2006) and Portelli and Nasuto (2008) gave us some important clues that a low cost event marker for EEG based data acquisition can be tried and tested in a laboratory. We endeavored to perform experimentation by using a mechanical keyboard such that a press of one key on a keyboard would start the stimulus presentation system on one system while simultaneously putting a label on the data acquired using data acquisition software Acq. Any mismatch would lead to the loss of information on the computer system being used to acquire physiological signals. However, before we proceed to describe the low cost event marker it is imperative to illustrate some important related studies. A brief review in this section describes the studies determining delay time incurred when using PS/2 and USB keyboards for real time applications.

2.3.1 Related Studies

In psychological experiments keyboards, joysticks and mouse are most commonly used as response devices. The response devices such as keyboards and joysticks have different scan frequencies. In real time applications such devices are bound to have some response delay. Shimizu (2002) determined the response delays for keyboards and joysticks. The clocks of a computer system were raised to a micro-second precision to determine the delay time of keyboards with different scan frequencies. It was concluded that the keyboards with higher scan frequencies are bound to have lower mean time delay as compared to the devices with lower scan frequencies. The mean time delay is calculated as a sum of three types of time delays (Equation 2.1).

$$\textit{Mean time delay} = \textit{physical time delay} + \textit{variable time delay} + \textit{fixed time delay} \qquad 2.1$$

1) The physical time delay is the time delay between making a physical contact and the key turning ON.

2) The variable time delay is the time after which the turned ON key is detected. This time delay depends on the scan frequency of a keyboard. A key pressed before the scan signal is immediately recognized; otherwise, it waits for the next scan signal.

3) The fixed time delay is the time required to convert the ON signal of a key into a character and the time required to transfer it to the CPU.

Ramadoss and Hung (2008) performed an experiment to check who among USB and PS/2 type of devices are more suitable for real time applications. The experimentation included both USB and PS/2 keyboards and USB and PS/2 mice to check the suitability for real time control applications. The evaluation of these devices was done by experimenting on two types of computer systems, one of the systems had an Intel core processor, 1 GB RAM, 120 GB hard disk and operating at 1.73 GHz clock frequency. The second computer system had a Celeron processor along with 512 MB RAM, 60 GB hard disk and operating at 2.4 GHz clock speed. The sensors of a robotic machine were connected to the computer systems for experimental analysis. While performing an experiment to determine the time taken to read the characters from the keyboards, it was found that the PS/2 and USB keyboards gave very similar results, and the average time for PS/2 keyboards was better by 2 millisecond on machine 1, whereas the results on the second system were same for both types of keyboards. Since the results are not clearly in favour of PS/2 keyboards further experimentation is needed to choose between USB and PS/2 keyboards while keeping application under consideration.

Portelli and Nasuto (2008) developed an inexpensive microcontroller-based synchronization module to synchronize the two computer systems, one used for presenting a stimulus to the subject and the other used to acquire an EEG of the subject being stimulated. The sync circuitry was interfaced to the computer system acquiring the EEG of a subject through a PS/2 port and to the stimulus presentation system through a serial driver chip (Max232) to enable RS232 serial communication. The designed sync required the programming of a PIC 16F877A microcontroller to detect a key press and then transfer the signal to both computer systems. The execution time required by the PIC processor to execute the instructions added to the serial transfer rate of the data using RS232 communication protocol. The computation of the delay times incurred in transferring the data from the keyboard to microcontroller (through polling) and the EEG presentation system (using PS/2), and then the transfer of data from the microcontroller to the stimulus presentation system added up to much lesser than 7.812 millisecond. The keyboard transfer rate lied between 10 kHz and 16 kHz, depending on the type of data being transferred. The debounce time while interfacing the keyboards with microcontrollers, usually between 20 and 30 millisecond, was not considered. Considering similar methodology for computing the time difference in making the mark on EEG acquisition system and starting the stimulus presentation system, particularly the operating speed of keyboard (10 kHz), the time difference would theoretically be always less than 1 millisecond, as no other added hardware is used.

It can be concluded from the above studies that no definite information on time delay to transfer a character from a keyboard to two computer systems is available. Further, we wanted to see if we can use two mechanically connected keyboards for simultaneously starting the stimulus presentation system and putting a label mark at that instant with press of a single key. With no particularly specific literature available for such type of experiments we made our own setup and designed a key detection program on a Dev C ++ platform. Below here we are describing the experimental setup, detecting the time of pressing of a key with precision on two computer systems and determining the difference in the latencies and importantly how the windows can be used for real time applications.

2.3.2 Experimentation Procedure and Result Analysis

Our objective is to acquire EEG signals time locked with the stimulus presented to subjects. To achieve this objective we used two mechanical keyboards and mechanically connected the F5 function key of both the keyboards. We programmed the Neurobs Presentation in such a manner that pressing F5 starts the stimulus on one computer system while simultaneously inserting an event mark on data being acquired using Biopac provided Acq 4.2. The experimental setup to study the difference in time between the generated mark and the start of a stimulus on pressing of a key is shown in Figure 2.6.

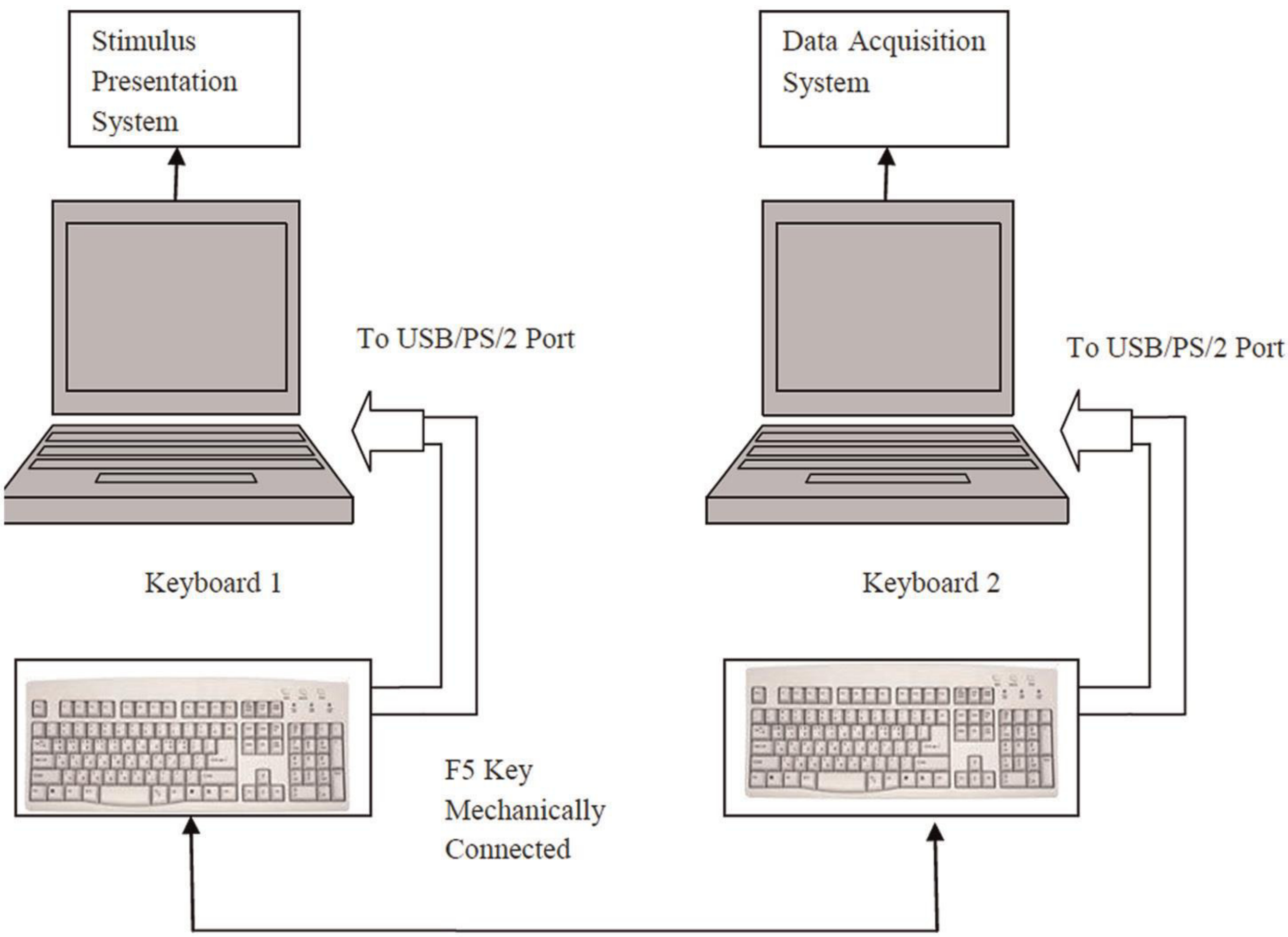


Figure 2.6: The experimental setup used for synchronized recording of EEG signals

The computer systems used in the study had similar specifications. Both the computer systems were Dell i5 computers containing 4 GB RAM, 500 GB hard disk drive and operating at 3.20 GHz clock speed. Both computers were loaded with the Windows 7 operating system. As far as Windows operating system is concerned, it is worth mentioning that the Windows operating system has not been designed for real-time applications and in applications where sub-millisecond precision is required it can result in errors. A study by Ramamritham et al. (1998) proved helpful in this regard. The operations can be improved in such cases where high precision is required by selecting a priority 'HIGH PRIORITY' for the selected process. This gives more precedence to the selected process over other processes operating under Windows. For real-time applications, the REAL TIME priority can be selected through a command window by using the command 'start/realtime name.exe'. Here 'name' refers to the process operation to be executed by Windows.

We started the experiment by raising the clocks of two computers to micro-seconds precision. Further the clocks of the machines were synchronized with time.windows.com. The key detection program was written on a Dev-C+ + platform, outputting time in micro seconds whenever the key was pressed.

The program was loaded into the two computer systems and executed. Before experimentation, all the animations running on the computer systems were turned off. The keyboards were then connected to the two computer systems through their USB/ PS/2 ports.

2.3.3 Experiment 1: Results and Analysis of USB Keyboards

The first experiment involves the analysis of two USB based keyboards with F5 keys mechanically connected. The key detection program was run on both the computer systems. Each time the F5 key of one of the keyboards was pressed, the time latency at which the press occurred was recorded on two computer systems using our program. The latency output obtained for about 420 keystrokes on both the computers was used to obtain the difference in synchronization between the two keyboards. The results obtained for the two USB keyboards after arranging the Synchronization Error (SE) in descending order are shown in the Figure 2.7.

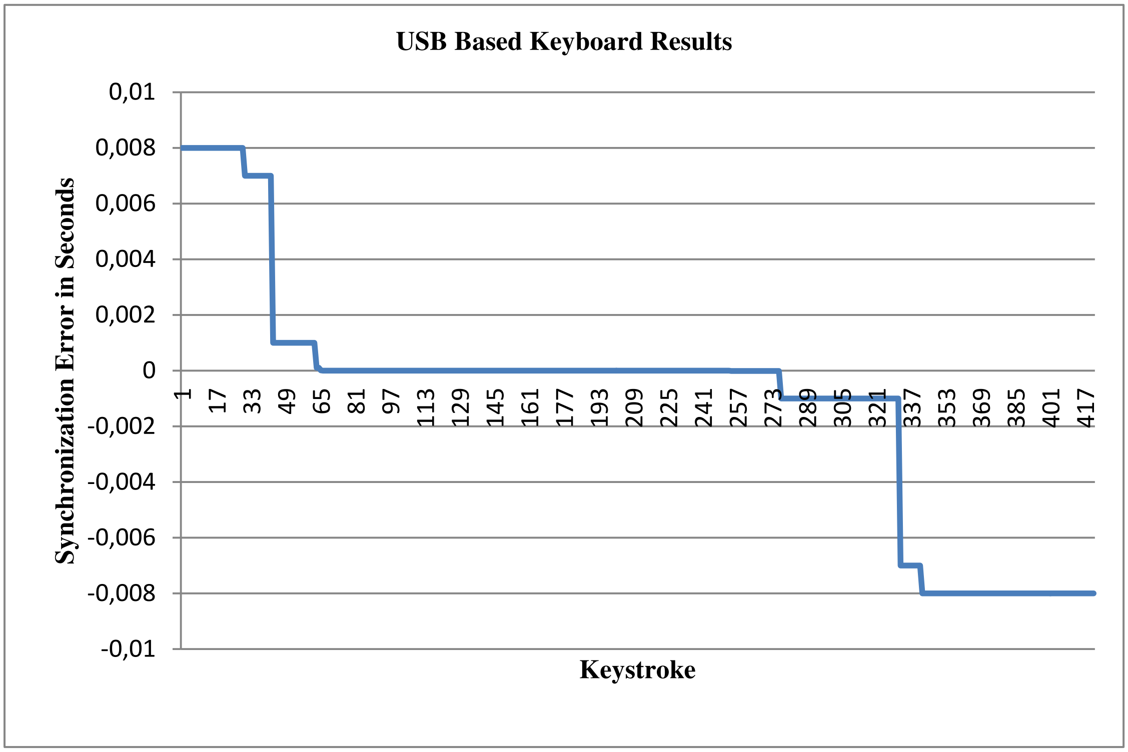


Figure 2.7: Synchronization error between two USB keyboards with key F5 mechanically connected to each other

The Figure 2.7 shows SE for 421 keystrokes of function key F5. It can be seen that the error remains between +8 milliseconds and -8 milliseconds for the whole experiment. Further for 289 keystrokes, the SE remained between +0.001second and -0.001second i.e. SE $\leq |0.001|$ second. Thus, the probability of occurrence of SE between ±0.001 second comes out to be 68.64%. For 138 keystrokes, the SE was zero and for 50 key strokes the SE was equal to ±.000001 second. It is interesting to see that the SE values obtained for USB keyboards are a set of discrete values such as ±0.001, ±0.000001, ±0.00001, 0, 0.0001(for two key strokes only), ±0.007 and ±0.008 second.

2.3.4 Experiment 2: Results and analysis of PS/2 keyboards

The same experimentation was performed using PS/2 keyboards. The Figure 2.8 shows

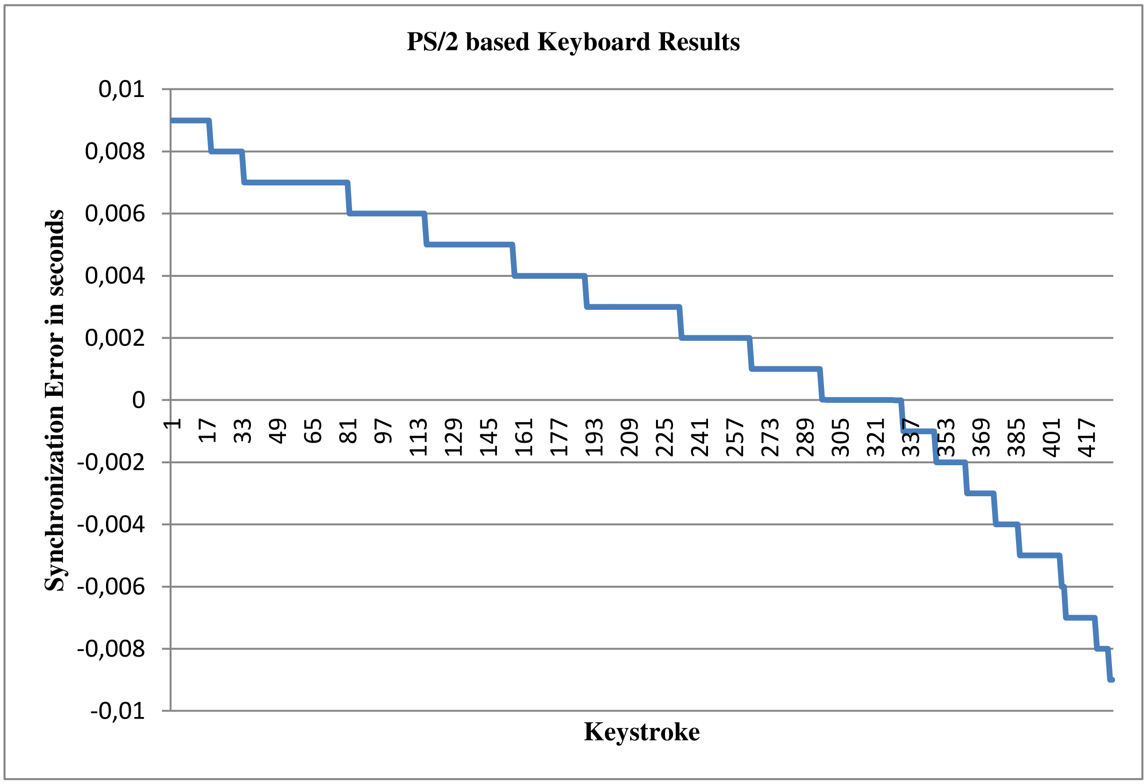


Figure 2.8: Synchronization error between two PS/2 keyboards with key F5 mechanically connected to each other

the difference in latency values obtained on two computer systems for F5 keystrokes. Unlike the latency differences for various keystrokes on mechanically connected USB keyboards, the synchronization curve obtained for experimentation on PS/2 keyboards after arranging the synchronization error (SE) in descending order shows that the error values were well distributed in the range of ±0.009 second unlike the case with the USB keyboards. A SE of ±0.001 second has been obtained for 84 key strokes of the common F5 key. If we make a comparison between Figure 2.7 and Figure 2.8 it can be seen that the probability of occurrence of SE below or equal to ±1 millisecond is only 19.5% as compared to USB keyboards where the probability of occurrence of SE at or below ±1 millisecond is high. It is as well pertinent to mention here that the SE for a keystroke (in second) could take on any value (in millisecond) between ± 1, ±0.1, ±0.01, ±0.001, ±2, ±3, ±4, ±5, ±6, ±7, ±8 or ±9.

2.3.5 Conclusion from Experiment 1 and Experiment 2

Our objective is to synchronize a stimulus presentation system with a data acquisition system. We designed our experiments such that pressing F5 key on any of the mechanically connected keyboards (particularly F5 key in our experiments) would start the stimulus presentation to subjects putting a label mark on EEG data at the same time. We determined the difference in latency values obtained on two computer systems after F5 key is pressed. The results show that the probability of occurrence of latency difference below ±0.001 second is higher with USB keyboards as compared to the PS/2 keyboards. The results thus favour the usage of USB keyboards for acquisition of physiological data in response to external stimuli as compared to PS/2 keyboards. Apart from this we also described in this section how windows can be used for real time applications and high priority should be assigned to the tasks such as data acquisition. The successful experimentation has helped us save costs to the tune of $3000. We conducted two case studies using the synchronization setup. The first case study involves the acquisition of EEG signals for emotion recognition using IAPS stimulus and in the second case study the EEG data has been acquired after an intervention to bring the subjects from low valence high arousal to high valence low arousal state. The case studies are described in Chapter 3 and Chapter5.

2.4 Acquisition of EEG Signals for Emotion Recognition

With results favouring synchronization setup involving USB keyboards, a data acquisition operation was started. The Table 2.1 shows the criterion used for selection of IAPS images belonging to LVHA, HVHA, HVLA and LVLA classes of emotion. An epoch time of 2.5s was selected in reference to a study of Frantzidis et al. (2010). The Figure 2.9 shows an epoch selection of 2.5 second.

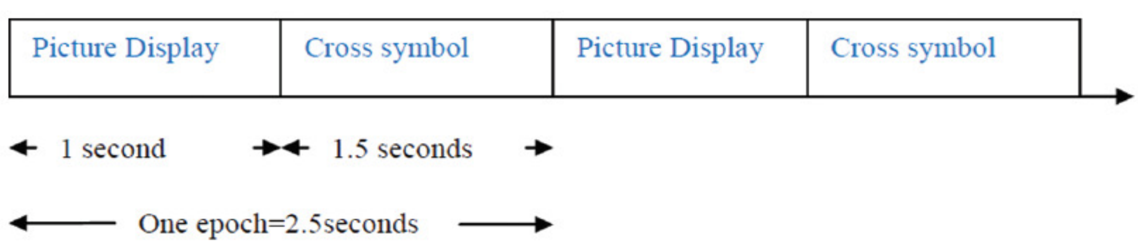


Figure 2.9: The image presentation protocol

An evocative stimulus belonging to a particular class was shown for 1 second followed by a cross symbol for 1.5 second. The process was repeated in a consecutive manner with images from other classes shown to subjects in a similar manner. A more elaborative description related to image presentation is shown in Figure 2.10.

We started emotion stimulus presentation with LVHA image. Each stimulus was presented for 1 second followed by a cross symbol of 1.5 second. The stimulus was presented in such a manner that one of the ordinates did not vary. For example, between LVHA and HVHA stimulus arousal was high, between HVHA and HVLA valence was high, between HVLA and LVLA arousal was low and between LVLA and LVHA stimuli valence was low.

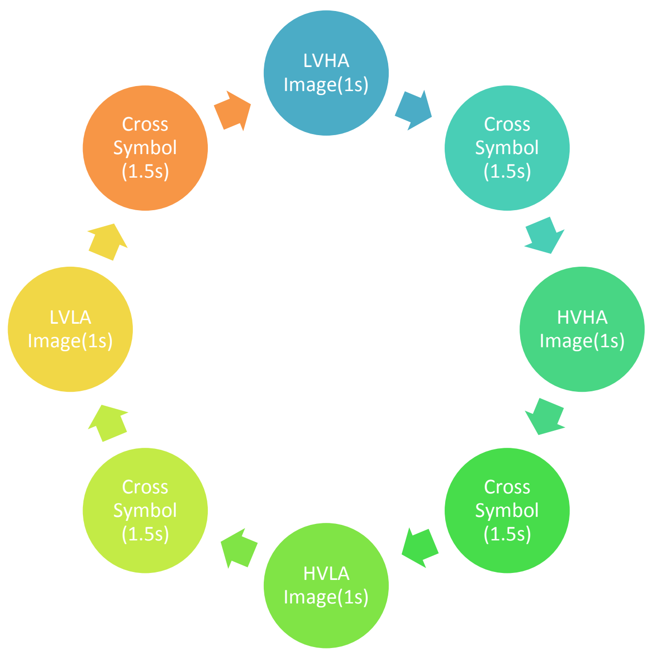


Figure 2.10: Sequence in which emotion evoking images were presented to the subjects

2.4.1 Hardware used for Acquiring EEG

The Biopac provided wearable EEG cap 100C containing 20 electrodes including a cap ground placed according to 10-20 International System was used for acquiring EEG signals. The electrode cap was fixed to Biopac MP150 system containing 10 biomedical instrumentation amplifiers. An electrolyte gel was used to maintain the electrode impedance below 10k ohms. The EEG data analyzed in this study has been acquired from 24 male students of Thapar University, Patiala. All the subjects were right handed males with normal to corrected vision and were in the age group of 18 to 24 years. None of the subjects reported any previous mental or psychological illness. We chose left mastoid as a reference electrode. The EEG data analyzed in this study has been acquired from 10 electrodes namely Fz, Cz, Pz, Fp1, Fp2, F3, F4, P3, P4 and F8 on a Biopac provided Acq Knowledge platform. More description about EEG cap 100C can be read from https://www.biopac.com/wp-content/uploads/EEG-CAPS.pdf. The 10-20 placements of the electrodes are shown in Figure 2.11.

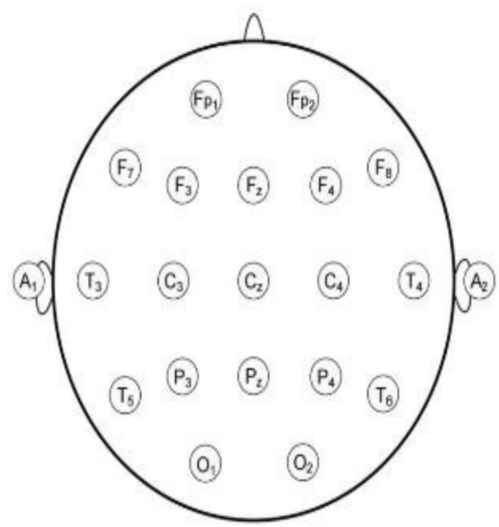


Figure 2.11: The 10-20 placement of electrodes on EEG 100C cap

The Figure 2.12 shows Biopac system used in our experiments. More information about MP150 system can be had from https://www.biopac.com/wp-content/uploads/MP150-Systems.pdf. The protocol required the subject to be seated in front of the computer screen where the emotion evoking stimuli was being presented. As we were interested in ERP analysis of the acquired EEG signals, it required the stimulus and the acquired EEG signal to be exactly time locked. We achieved this by mechanically connecting two keyboards on F5 key and then connected one of the keyboards to the USB port of the computer system running a presentation system (computer 2) and the other to the computer system being used to acquire an EEG signal (computer 1).

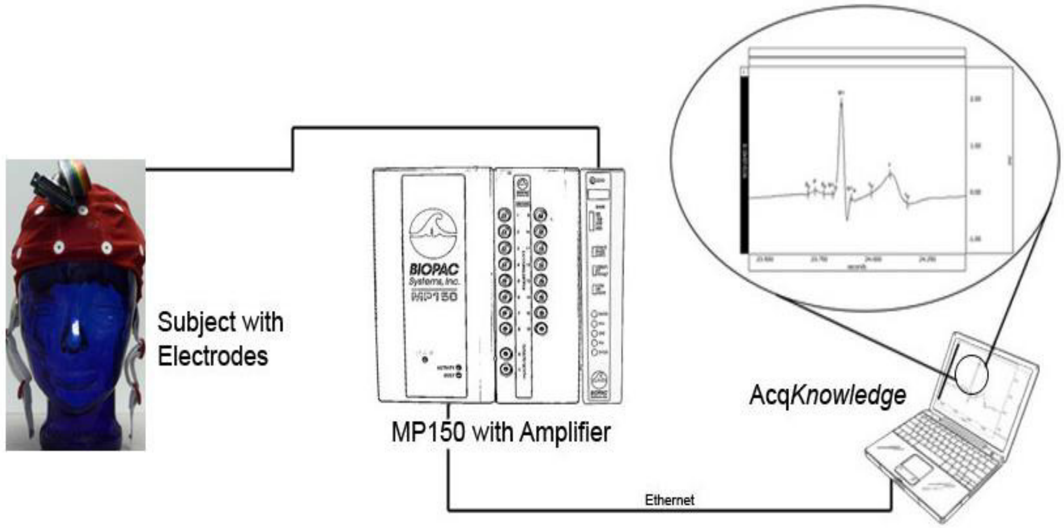


Figure 2.12: Biopac MP150 system in conjunction with EEG cap 100C used in this study

Pressing F5 key on one keyboard connected to one system invoked the similar response on the parallel keyboard connected to the second device. Pressing F5 key on the setup as shown in Figure 2.6 started the presentation of stimulus to the subjects at the same time putting a latency mark on the acquired data. The presentation stimulus generated a time log sheet indicating the precision as well as the time for which each image has been shown to the subjects. A snapshot of the log file generated along with the acquired EEG signal is shown in Figure 2.13.

With the time of beginning of stimulus known to us (a first mark placed on acquired EEG using F5 key) and the log sheet generated by the Presentation software indicating the time length of each trial from among the 160 total trials, the EEG signal corresponding to each stimulus could be marked, extracted and processed corresponding to each trial. An EEG signal of more than 400 second yielded satisfactory results with no loss of time. The circled time shows the image when the F5 key was pressed.

In Figure 2.13, the time column shows the time of presentation of stimuli (in milliseconds) calculated in reference to the time at which the presentation program was executed. The time uncertainty (dT) points to the occurrence of presentation event between time T and T+dT. The trial time shows the time between the start of presentation program and pressing of the F5 key (i.e. the start of the image presentation to the subject).

trial	event_type	code	time	trial_time	time_uncertainty	duration
1	Picture	Waiting on Button Press	6.8	0	0.1	3792.4
1	Response	1	3793.2	3786.4	0.1	-1
2	Picture	1019.jpg	3799.2	0	0.1	1006.9
3	Picture	Pre Stimulus	4806.1	0	0.1	1510.3
4	Picture	3053.jpg	6316.4	0	0.1	1006.8
5	Picture	Pre Stimulus	7323.2	0	0.1	1510.3
6	Picture	4250.jpg	8833.5	0	0.1	1006.8
7	Picture	Pre Stimulus	9840.3	0	0.2	1510.3
8	Picture	1441.jpg	11350.6	0	0.1	1006.9
9	Picture	Pre Stimulus	12357.5	0	0.1	1510.3
10	Picture	9220.jpg	13867.8	0	0.1	1006.8
11	Picture	Pre Stimulus	14874.6	0	0.1	1510.3
12	Picture	3080.jpg	16384.9	0	0.1	1006.8
13	Picture	Pre Stimulus	17391.7	0	0.1	1510.3
14	Picture	4210.jpg	18902	0	0.1	1006.9
15	Picture	Pre Stimulus	19908.9	0	0.1	1510.2
16	Picture	5760.jpg	21419.1	0	0.1	1006.9
17	Picture	Pre Stimulus	22426	0	0.1	1510.3

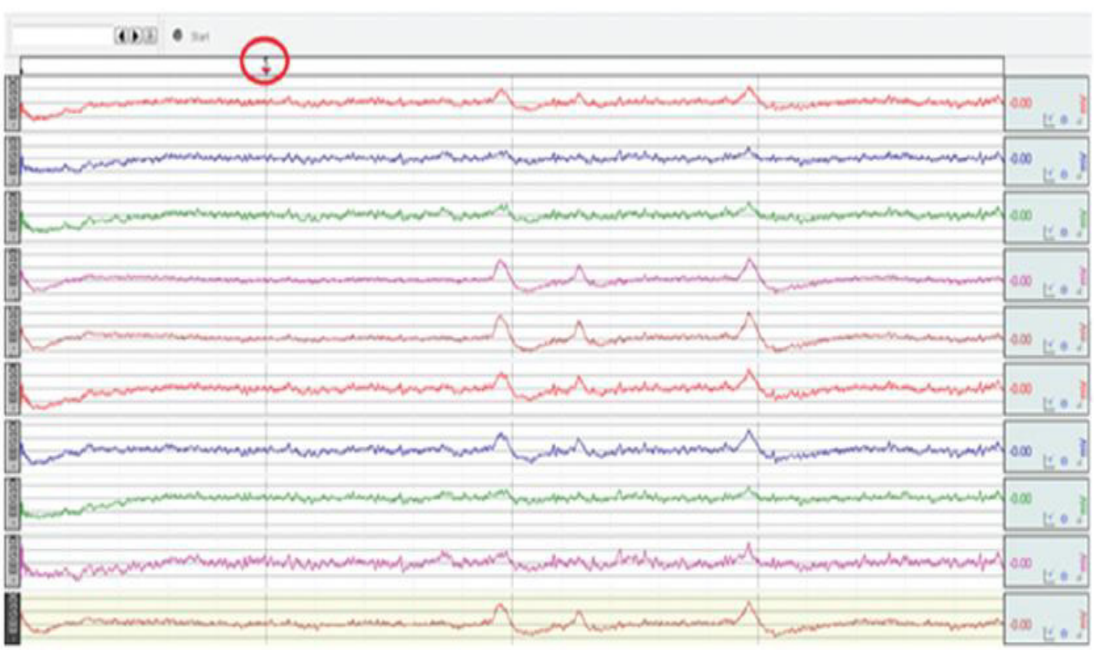


Figure 2.13: The log file generated and a mark placed on pressing F5 key

The duration column in the log file shows the period (or stimuli length in milliseconds) for which the stimulus (evocative image or cross symbol on white screen) was shown to the subjects. As both the keyboards were interfaced with high-end computers, the presentation software was programmed to display the first image just after the image with the plus symbol on the press of the F5 key. This press of a key was simultaneously detected by the EEG acquisition system and a mark was placed at that instant.

During the experimentation, all non-essential system services and running software were stopped on the computers in use. The log file generated for the set of images can now be analyzed to determine the timeframe for EEG with respect to the epoch time.

2.4.2 Preprocessing Operations on EEG and Attribute Extraction

The offline filtering operations have been performed on EEG signals. The filtering operations are as well influenced by the study that showcased highest results obtained when using ERPs as attributes (Frantzidis et al., 2010). To remove the interfering power noise a notch filter has been used to remove power noise of 50 Hz. To obtain the EEG signals in a frequency range of 0.5 to 40 Hz, IIR low pass filter with a cut off frequency of 40 Hz and IIR high pass filter with a cut off frequency of 0.5 Hz have been used. The subjects were advised to not to move or blink their eyes during the presentation of a stimulus. We in fact showed to them how the EEG varied due to blinking of eyes. The subjects remained attentive during the stimulus presentation and moved or blinked their eyes in the span of 1.5 second during the presentation of a cross symbol. We did not use ICA and artifact removal techniques (Selvan and Srinivasan, 2000; Kumar and Anand, 2006; Daly et al., 2013) in accordance with conclusion of Jenke et al. (2014) as these operations did not reportedly impact the classification results considerably but added to offline processing time. The filtering operations as well as feature extraction procedure have been performed using Acq4.2 software provided by Biopac. The EEG signal acquired for each image has been used to determine the single-trial ERP values. The averaging of the signals belonging to a particular class of emotion yielded average ERPs for classification into four classes. The Table 2.2 and Table 2.3 shows the sample of single-trial ERP and latency values respectively, acquired from one of the subjects.

Table 2.2: ERP values for 9 trials

Stimulant → ERP in mV↓	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
P100	0.173	0.176	0.158	0.195	0.162	0.200	0.195	0.194	0.200
N100	0.182	0.197	0.169	0.203	0.175	0.203	0.213	0.202	0.208
P200	0.166	0.153	0.151	0.182	0.164	0.193	0.178	0.195	0.177
N200	0.175	0.167	0.162	0.191	0.171	0.199	0.202	0.203	0.189
P300	0.135	0.135	0.136	0.165	0.143	0.174	0.165	0.171	0.158
N300	0.142	0.142	0.143	0.168	0.150	0.191	0.175	0.185	0.163

Table 2.3: Latency values for 9 trials

Stimulant → Latency in ms↓	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
LP100	120	80	120	98	80	120	120	112	100
LN100	80	108	80	120	120	84	80	80	120
LP200	220	220	210	220	220	220	220	220	208
LN200	196	180	186	204	196	188	180	180	180
LP300	302	298	292	320	294	282	292	320	320
LN300	320	316	316	288	316	310	314	280	280

* LP: Latency for the positive (P) ERP, LN: Latency for the negative (N) ERP

The stimulant in the Table 2.2 describes the number of an image. As a total of 160 images have been shown, the data has been collected for each single trial. The single-trial attributes for nine consecutive images (from a total of 160 images) shown to one of the subjects are shown in Table 2.2 and Table 2.3. Here P stands for positive and N stands for negative, whereas 100, 200 and 300 describes the latency. P300 means the local maxima obtained after 300 ms of the onset of stimulus (Luck, 2005). Similarly, N stands for local minima at the described latency. LP100=120 ms means that the latency value is 120 ms, corresponding to P100=0.173 mV.

The synchronization setup proved helpful in acquiring and analyzing EEG signals for the purpose of studying emotion transition among the subjects.

2.5 Summary

This chapter describes execution of one of the objectives related to the acquisition of EEG signals for recognition of emotions. The core of this chapter is development and testing of synchronization setup. The synchronization setup has been developed by mechanically connecting two keyboards at F5 key. To detect the time when a key is pressed, an algorithm in Dev-C++ has been developed and executed on two time synchronized computer systems. The algorithm detected the pressing of F5 key on any keyboard and provided us with latency values. The difference of the latency values recorded from two computer systems produced the synchronization error. The synchronization error results of USB and PS/2 keyboards have been explicitly explained. The synchronization error for USB keyboards did not exceed ±8 millisecond whereas our window of ERP is ±20 millisecond and hence the error of this magnitude is acceptable.

The tested synchronization setup has been used for acquisition of EEG signals. The pressing of F5 key started the stimulus presentation and generated a label mark on the acquired EEG. The Chapter 2 also describes the criteria of stimulus selection from among the IAPS images, emotion presentation protocol followed and hardware used to acquire EEG signals in our experiments. Each subject experienced 160 emotion evoking trials belonging to four classes of emotions and provided us with self assessment on a scale of 1 to 9 (Arousal and Valence) for each trial. The EEG signals have been filtered to remove power noise of 50 Hz and to bring EEG signals in the useful range of 0.5 Hz to 40 Hz. The ERP attributes, namely, P100, N100, P200, N200, P300, N300 and corresponding latencies have been acquired from single trial as well as average EEG signals using Acq 4.2 software. The analysis of EEG signals thus acquired is described in Chapter 3 and Chapter 4.

CHAPTER-3

CLASSIFICATION OF EMOTIONS USING EEG SIGNALS FROM CENTRAL ELECTRODES

3.1 Introduction

The use of EEG signals for classification of emotions is in vogue today. The development of real time emotion classifiers using few of the EEG electrodes is catching the fancy of biomedical engineers and psychologists. The single trial EEG signals have been acquired and analysed successfully by many biomedical engineers and scientists working in the field of emotion generation and classification. The studies by Koelstra et al. (2012), Koelstra and Patras (2013) and Soleymani et al. (2015) compare the use of EEG features particularly power bands with facial and eye gaze features. Though the accuracy results of both the studies are contrasting but the use of single trial EEG signals in recognition of emotions have been appositely illustrated. The contrasting results may be due to use of different feature selection techniques and different electrodes chosen. Koelstra and Patras (2013) rated frontal electrodes on top for recognition of emotions along arousal and valence axis. Our study has been highly influenced by the study of Frantzidis et al. (2010) in which only three electrodes along the central line namely Fz, Cz and Pz were used for extracting ERPs to classify emotions along arousal and valence axis. Therefore, we first decided to acquire EEG signals in a manner Frantzidis et al. (2010) had done. However, the studies on DEAP and MAHNOB HCI data prompted us to test single trial EEG signals for emotion classification as well. Zhang et al. (2013) used rapid visual presentation paradigm on 16 right handed subjects of which nine were females by using images from Chinese Facial Affective Picture System (CFAPS) (Gong et al., 2011). Zhang et al. concluded that the variations in single trial ERP amplitudes between experimental conditions formed the basis of variations in average ERP amplitudes such as P1, N1, N170, Vertex Positive Potential (VPP), N3, and P3. The experimentation protocol followed for emotion elicitation by Zhang et al. (2013) is different from proposed study, but still the substantial variation in average ERP amplitudes due to single trial ERP amplitudes had been reported by Zhang et al. It is noteworthy to mention that apart from other electrodes placed on the scalp, the electrodes placed along the central line such as Fz, Cz and Pz electrodes appeared for ERP study in work proposed by Zhang et al. (2013).

In another study to detect the most relevant scalp regions for classification of emotions, Hidalgo-Muñoz et al. (2013) collected EEG signals from 26 female subjects by using IAPS images for emotion evocation. The images belonging to each class of LVHA and HVHA were selected in a manner that arousal rating of each image was more than 6 but valence rating was more than 6.5 for HVHA images and it was lower than 2.71 for LVHA images. It is worth mentioning over here that epoch time of presented stimuli was 3.5 second including the stimulus presentation time of only 0.5 second and a black screen for 2.25 second. The pre stimulus cross symbol was presented for 0.75 second. Each image was presented 3 times. The EEG data was acquired from 21 electrodes namely Fp1, Fpz, Fp2, F7, F3, Fz, F4, F8, T7, C3, Cz, C4, T8, P7, P3,Pz, P4, P8, O1, Oz and O2 in accordance with 10-20 International System using Easy-Cap in reference to a nose electrode. The EEG data acquired at a sampling frequency of 1000 samples per second was resampled to 250 samples per second and brought in a usable range of 0.5Hz to 60Hz by using forward and reverse Butterworth filters. The power line noise of 50 Hz was removed by using a notch filter. Averaging of the time locked epochs in reference to the onset of stimulus was obtained for each subject to obtain two signals belonging to LVHA and HVHA class. The instantaneous power features were determined in various frequency bands for whole frequency range using Mortlet wavelet technique. The features were reduced by using SVM-RFE technique. The features selected using both RFE and t-test were used for classification of valence domain using Leave One Out (LOO) cross validation technique. It was found that the majority of the features selected lied in the time region of 300 - 500 milliseconds. The contribution of each channel to the selected features is shown in Figure 3.1. It can be seen from Figure 3.1 that among frontal electrodes Fz, among central electrodes Cz, among parietal electrodes P3 and among occipital electrodes O1 have contributed the maximum percentage of features for valence recognition. Pz is the second best electrode as can be seen in Figure 3.1.

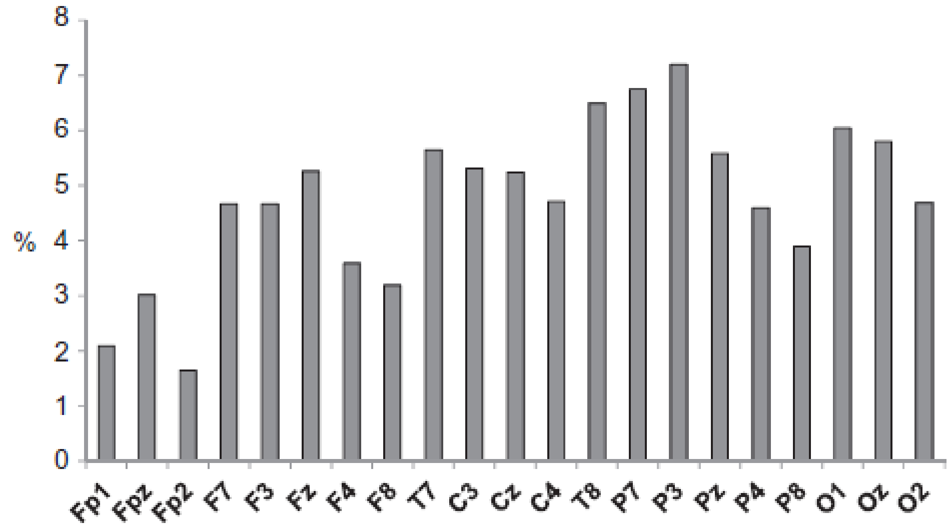


Figure 3.1: Contribution of each EEG channel to the 10% most relevant features (Hidalgo-Muñoz et al., 2013)

Thus we have chosen to develop an emotion classifier on those electrodes that are bound to give majority of features for emotion classification.

Since we are using single trial EEG signals for emotion classification, the subject dependent analysis has been performed as per the observations of Sarvan et al. (2006), Horlings(2008), Koelstra et al. (2012), Koelstra and Patras (2013) and Soleymani et al. (2015).

We have performed both subject dependent and subject independent studies using SVM polynomial classifier. This Chapter describes the development of subject dependent emotion classifier based on single trial ERPs, subject independent emotion classifier based on single trial ERPs, subject independent emotion classifier based on difference of single trial ERPs, subject independent emotion classifier based on average ERPs and subject independent emotion classifier based on difference of average ERPs by using features from central electrodes viz; Fz, Cz and Pz. The emotion classifiers developed on other combination of electrodes are described in Chapter 4.

3.2 Data Acquisition Methodology

The data acquisition setup involving Biopac provided EEG cap 100C in conjunction with Biopac MP150 system has been used for acquiring EEG signals on 10 electrodes at a sampling frequency of 500 samples per second. The complete setup including the synchronization hardware is described in Figure 2.6 in Chapter 2. The time locked EEG signals with epoch time of 2.5 second have been acquired for 160 trials belonging to four classes of emotions. The single trial EEG signals thus obtained have been filtered using IIR low pass and high pass filters to bring them in the range of 0.5 Hz to 40 Hz. The ac power noise of 50 Hz has been removed using a notch filter. The processed EEG signals are now used for feature extraction.

The 12 single trial ERP and latency attributes have been determined from an EEG signal corresponding to every image rated into four classes by the subject. The ERP features are acquired immediately with the onset of stimulus. The Table 3.1 shows the ERP features acquired from EEG signals in different time windows along with nomenclature followed in this study.

Table 3.1: The ERP features acquired from EEG signals and their nomenclature

Time Bracket	ERP acquired		Latency at which ERP has been acquired	
	Nomenclature for Maxima	Nomenclature for Minima	Nomenclature of Latency Value at which maxima has been obtained	Nomenclature of Latency Value at which minima has been obtained
80-120 ms	P100	N100	PT100	NT100
180-220 ms	P200	N200	PT200	NT200
280-320 ms	P300	N300	PT300	NT300

The ERP and latency features have been acquired within the time range of 80–120 ms, 180–220 ms and 280–320 ms after the start of the stimulus. The acquired features include P100, PT100, N100, NT100, P200, PT200, N200, NT200, P300, PT300, N300 and NT300. Here P stands for maxima, N stands for minima, PT/NT stands for latency value in ms at which maxima/minima has been obtained. For example, P300 is maxima in the time range of 280–320 ms and PT300 correspond to the time between 280–320 ms where P300 is observed. The ERP features thus acquired have been used for both subject dependent and subject independent studies. An overview of methodology and operations performed in this chapter are shown in Figure 3.2.

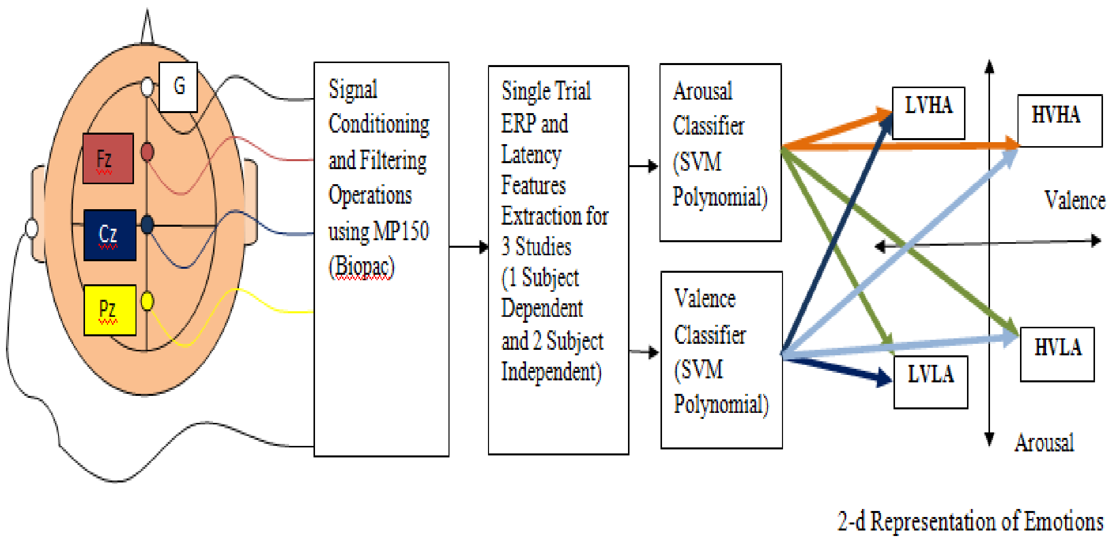


Figure 3.2: An overview of methodology and operations performed

3.3 Selection of Features

In subject dependent analysis, the test sample for every subject definitely consisted of 24 samples, with last 6 instances taken from each class of emotions. The attribute selection is done by testing different combinations of acquired features. All the ERP features [P100 N100 P200 N200 P300 N300 PT100 NT100 PT200 NT200 PT300 NT300] are initially selected for training a classifier. Accuracy of classification (Arousal or Valence) is determined on the test set. A new attribute set is selected by removing one of the attributes say P100. The classifier is again trained and tested. If the test accuracy using new attribute set is more than the previous one, new attribute set is retained and the previous one is ignored. A new attribute set is now generated by removing or retaining a new parameter and the accuracy using a new attribute set is now compared with previous one. This process of selecting features is continued till the classification accuracy does not increase further. The separate combinations of bio-potentials [P100 N100 P200 N200 P300 N300] and latencies [PT100 NT100 PT200 NT200 PT300 NT300] have as well been tried separately. The first combination for training and testing is obtained by using all ERPs [P100 N100 P200 N200 P300 N300], the second combination is obtained by using all ERPs except P100 i.e. [N100 P200 N200 P300 N300], the third combination by using all ERPs except P100 and N100 i.e. a combination [P200 N200 P300 N300] is used for training and testing a classifier. Similarly other combinations have been obtained from the ERPs, latencies and the combination of ERPs and latencies. The attribute set with smaller number of features is selected incase if two accuracies are equal. The training data for any subject consisted of the samples obtained after reserving the 24 samples (6 for each class) for testing and the instances rejected by the subject.

The SVM polynomial kernel in Matlab has been used to classify emotions along the arousal and valence axis. The training and testing have been done by using the instructions

svmtrainarousal=svmtrain(z1(trainindex,:),trainoutputarousal(trainindex), 'Autoscale, true, 'Showplot', false, 'Kernel Function', 'polynomial', 'polyorder',s, 'Boxconstraint',bestc, 'QUADPROG_OPTS',options); and

testoutput = svmclassify(svmtrainarousal,w1,'showplot',false);

The accuracy results presented in this manuscript have been obtained after performing 10-fold cross-validation on the training data. The best 'C' value thus determined is used for training on the full training set and then the classifier is tested on the test set. The output of the two SVM's performing classification of arousal and valence is combined to obtain a four class classification of the emotions. The classification technique is shown in Figure 3.3.

In a study done by Jenke et al. (2014), the average ERP attributes were not chosen for emotion classification as it increased the processing time requiring the averaging of EEG signals for each type of emotion. The attributes in this proposed study are determined directly from the EEG and neither averaging of EEG is done and nor any statistically extracted features have been used. This approach brings us near to develop a real time emotion classifier as the selection of the bio-potentials and latencies directly from EEG reduces the processing time to minimal.

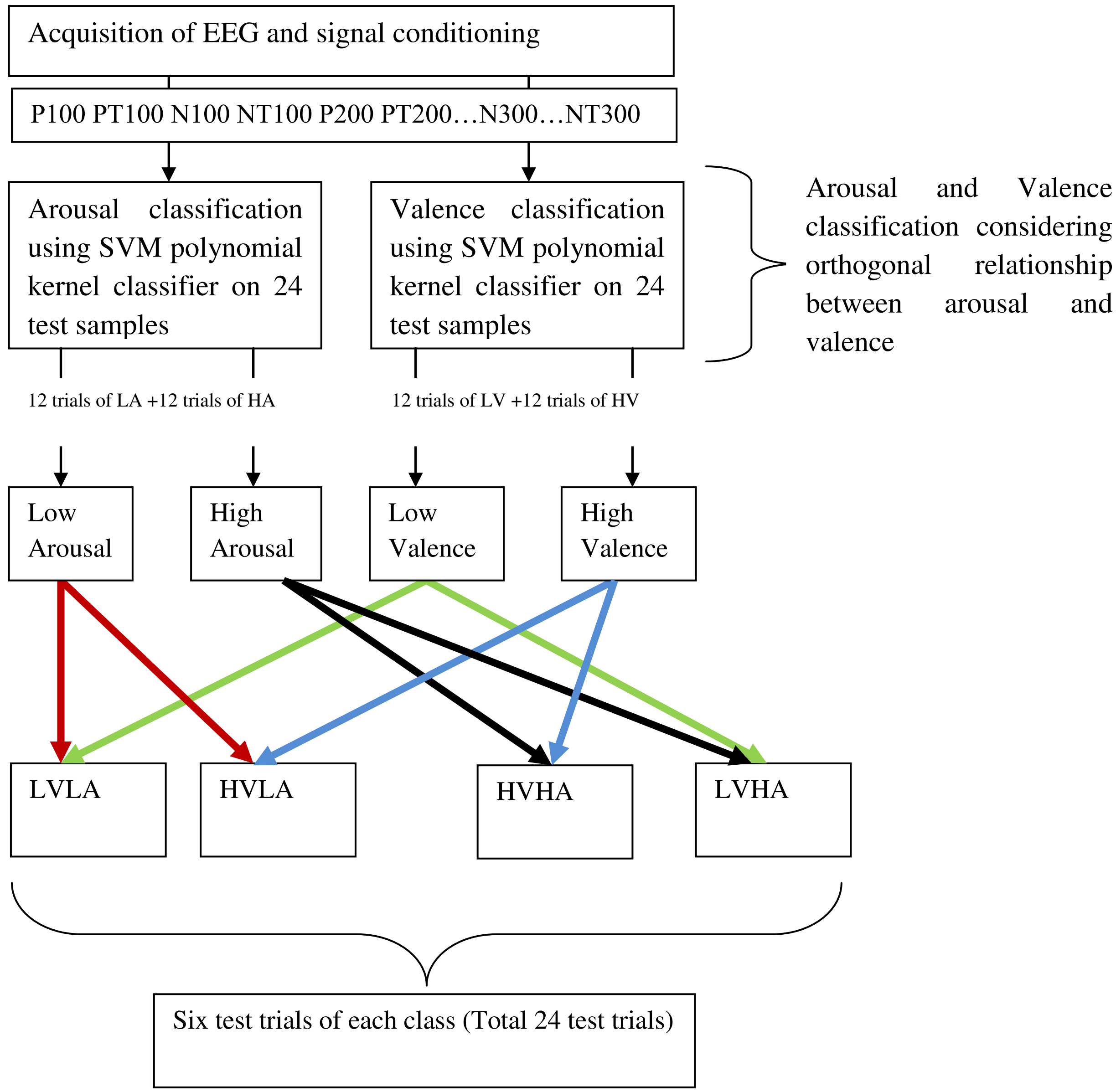


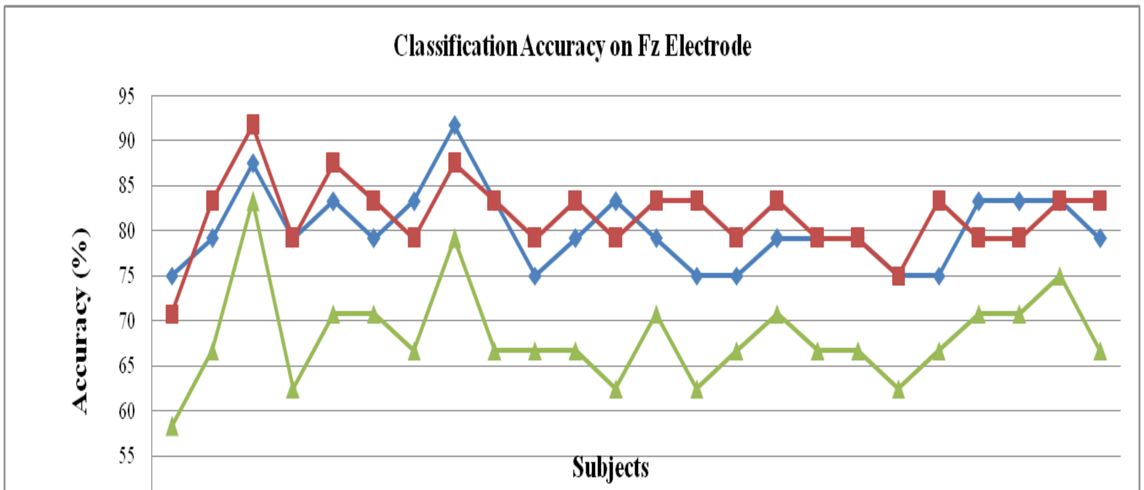
Figure 3.3: Classification methodology used in subject dependent study

3.4 Subject Dependent Emotion Classification Results

The evoked EEG signals obtained from 24 right handed male subjects have been used to study four class classification of emotion. The single trial ERP features have been analyzed to classify emotions along arousal and valence axis for each subject. An overview of the studies performed in this chapter is shown in Figure 3.3. For classification purpose SVM polynomial classifier has been used throughout this study.

(Frantzidis et al., 2010; Petrantonakis and Hadjileontiadis, 2010b; Sourina and Liu, 2011).

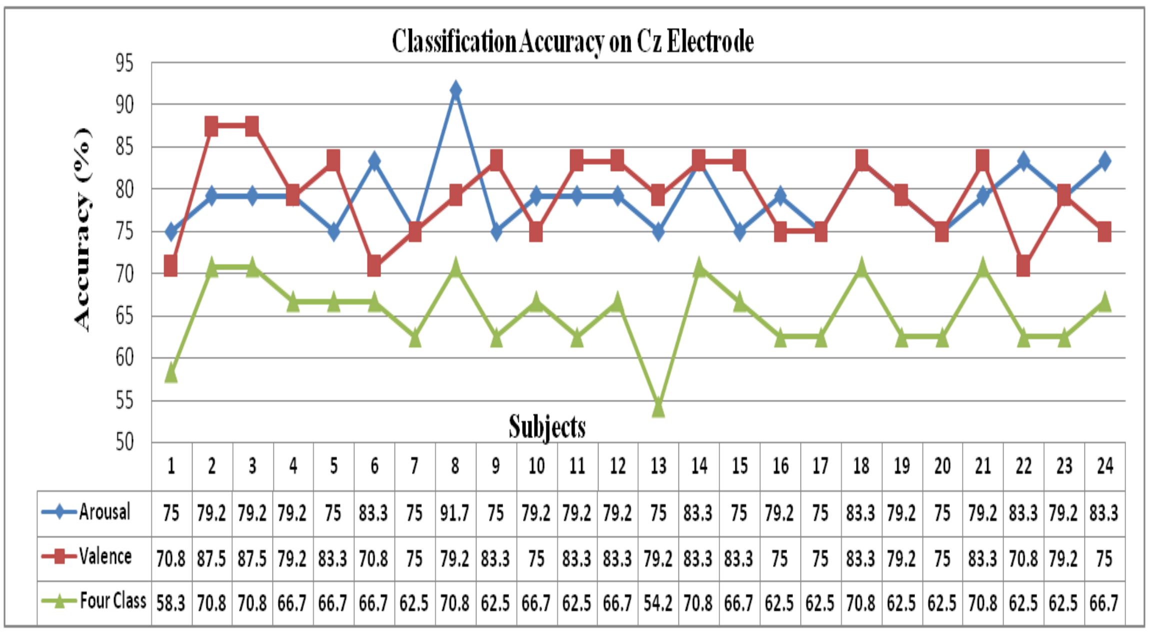
In this study emotion classification results have been explicitly described on three chosen electrodes. Each Figure shows the arousal classification, valence classification and four class emotion classification results in percentage. The Figure 3.4 shows emotion classification results obtained at Fz electrode for 24 subjects. It can be seen from Figure 3.4 that the average arousal classification accuracy on Fz is 80.2%, average valence classification is 81.6% and average four class classification is 68.2%. Arousal classification results lie in the range of 75 - 91.7%, valence in the range of 70.8 - 91.7%, and four class emotion classification results in the range of 58.3 - 83.3% have been obtained for 24 subjects.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Arousal	75	79.2	87.5	79.2	83.3	79.2	83.3	91.7	83.3	75	79.2	83.3	79.2	75	75	79.2	79.2	79.2	75	75	83.3	83.3	83.3	79.2
Valence	70.8	83.3	91.7	79.2	87.5	83.3	79.2	87.5	83.3	79.2	83.3	79.2	83.3	83.3	79.2	83.3	79.2	79.2	75	83.3	79.2	79.2	83.3	83.3
Four Class	58.3	66.7	83.3	62.5	70.8	70.8	66.7	79.2	66.7	66.7	66.7	62.5	70.8	62.5	66.7	70.8	66.7	66.7	62.5	66.7	70.8	70.8	75	66.7

Figure 3.4: Emotion classification accuracy results (%) on Fz electrode

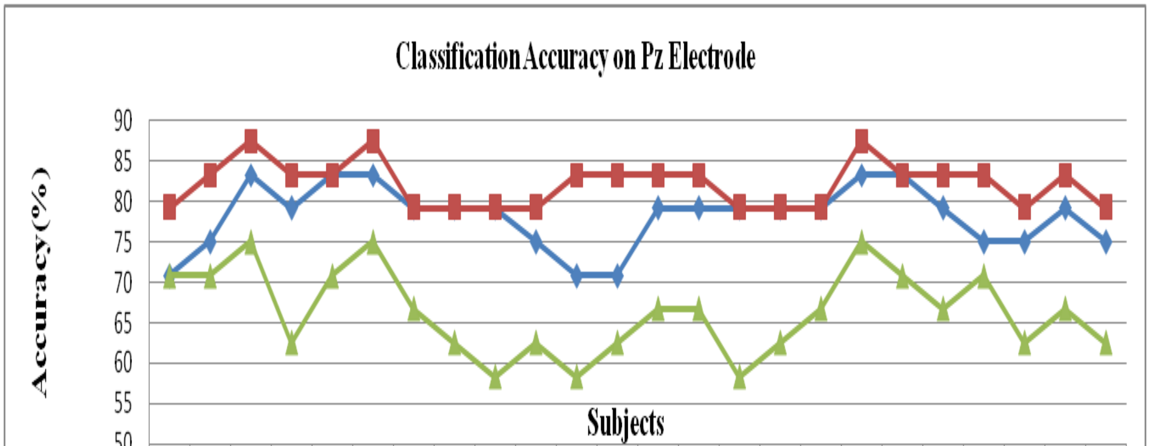
It can be seen that the best arousal and valence classification results described over here are above 70% in any case, however, the four class classification results depend upon the test trial accurately classified along arousal and valence domain. If the test trial is accurately classified along valence but not along arousal, the test trial will wrongly appear to be classified in say LVLA quadrant instead of actual LVHA quadrant. In other words, the four class classification accuracy has been determined considering only those samples which have been classified both along arousal and valence domains correctly. Similarly, arousal, valence and the four class emotion classification results obtained on electrode Cz is shown in Figure 3.5. It can be seen that arousal classification results lie in the range of 75 - 91.7%, valence classification in the range of 70.8 - 87.5% and four class emotion classifications in the range of 54.2 - 70.8% on Cz electrode. Average arousal classification and valence classification is 79.2% where as average four class classification accuracy is 65.1% for 24 subjects.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Arousal	75	79.2	79.2	79.2	75	83.3	75	91.7	75	79.2	79.2	79.2	75	83.3	75	79.2	75	83.3	79.2	75	79.2	83.3	79.2	83.3
Valence	70.8	87.5	87.5	79.2	83.3	70.8	75	79.2	83.3	75	83.3	83.3	79.2	83.3	83.3	75	75	83.3	79.2	75	83.3	70.8	79.2	75
Four Class	58.3	70.8	70.8	66.7	66.7	66.7	62.5	70.8	62.5	66.7	62.5	66.7	54.2	70.8	66.7	62.5	62.5	70.8	62.5	62.5	70.8	62.5	62.5	66.7

Figure 3.5: Emotion classification accuracy results (%) on Cz electrode

On Pz electrode (Figure 3.6), arousal classification accuracy lies in the range of 70.8 - 83.3%, valence classification is in the range of 79.2 - 87.5% and four class classification accuracy lies in the range of 58.3 - 75%. Average classification accuracy along arousal axis is 78.1%, along valence axis is 82.1% and average four class classification accuracy is 66.3%. If we compare the results on three electrodes then for any subject, the four class emotion classification is more than 62%.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
Arousal	70.8	75	83.3	79.2	83.3	83.3	79.2	79.2	79.2	75	70.8	70.8	79.2	79.2	79.2	79.2	79.2	83.3	83.3	79.2	75	75	79.2	75
Valence	79.2	83.3	87.5	83.3	83.3	87.5	79.2	79.2	79.2	79.2	83.3	83.3	83.3	83.3	79.2	79.2	79.2	87.5	83.3	83.3	83.3	79.2	83.3	79.2
Four Class	70.8	70.8	75	62.5	70.8	75	66.7	62.5	58.3	62.5	58.3	62.5	66.7	66.7	58.3	62.5	66.7	75	70.8	66.7	70.8	62.5	66.7	62.5

Figure 3.6: Emotion classification accuracy results (%) on Pz electrode

3.4.1 Statistical Analysis of Results

To check if obtained accuracy is higher than the expected random accuracy, the paired one tail t-test has been applied. On Fz electrode, comparing arousal classification results with expected value of 50%, we obtained a p value of 1.3×10^{-21}, 3.53×10^{-22} for low and high valence classification and 6.5×10^{-23} for four class emotion classifications on comparing the accuracy results with expected accuracy of 25%. Similarly on Cz electrode, the p values obtained are 8.8×10^{-22} while classifying arousal, 1.2×10^{-19} while classifying valence and 3.6×10^{-24} for four class classification. On Pz electrode as well, a p value of 9.3×10^{-22} is obtained for arousal classification, 3.1×10^{-26} for valence classification and 8.5×10^{-23} for four class classification of emotions. Since the p values determined with respect to expected values are much lesser than 0.05, it can be safely concluded that the obtained accuracy is higher than expected accuracy.

We have calculated the confusion matrix for each electrode as well. As described earlier, the test trial definitely consisted of 6 samples from each class of emotion namely LVHA, HVHA, HVLA and LVLA. So if we present the combined result of 24 subjects on each electrode, a total of 144 trials have been tested for a particular class of emotion. In other words the confusion matrix represents the results on each test trial conducted on subject and it makes a total of 6 trials of each class x 4 classes x 24 subjects=576 test trials in combination. The confusion matrix represented by Table 3.2 pertains to the classification results on Fz electrode. The Table 3.3 describes statistical parameters such as sensitivity, specificity, precision, negative predictive value and F1score for 24 subjects. In error analysis tables the statistical parameters have been described by the following formulas.

Sensitivity or True Positive Rate = True Positive (TP)/ (True Positive (TP)+ False Negative (FN)) i.e. Sensitivity = True Positive/ Total Positive

Specificity or True Negative Rate= True Negative (TN)/ (True Negative (TN) + False Positive(FP))

Precision or Positive Predictive Value (PPV) = T P / (T P + F P)

Negative Predictive Value = TN/ (TN+FN)

F1 Score = 2 T P / (2 T P + F P + F N)

Similarly, the confusion matrix and error analysis of subjects on Cz electrode are shown in Table 3.4 and Table 3.5 respectively. The results on Pz electrode are shown in Table 3.6 and Table 3.7.

Table 3.2: The confusion matrix on Fz electrode with single trial ERP attributes

Confusion Matrix on Fz electrode		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	95	21	11	17
	HVHA	12	100	27	5
	HVLA	7	30	88	19
	LVLA	15	9	10	110

The Table 3.2 shows good accuracy results on Fz electrode. The Sensitivity and Precision values are above 60% as shown in Table 3.3. The Higher Negative Predictive Values show that apart from true positives, true negatives are as well high.

Table 3.3: Error analysis on Fz electrode

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	66	92.1	73.6	89	69.6
HVHA	69.4	86.1	62.5	89.4	65.8
HVLA	61.1	88.9	64.7	87.3	62.9
LVLA	76.4	90.5	72.8	92	74.6

The F1 score is more than 0.6 for each class of emotion. Similarly, good results have been obtained for Cz electrode as shown in Table 3.4 and Table 3.5.

Table 3.4: The confusion matrix on Cz electrode with single trial ERP attributes

<table>
<tr><td colspan="2" rowspan="2">Confusion Matrix on Cz electrode</td><td colspan="4">Predicted Classes</td></tr>
<tr><td>LVHA</td><td>HVHA</td><td>HVLA</td><td>LVLA</td></tr>
<tr><td rowspan="4">Actual Classes</td><td>LVHA</td><td>96</td><td>21</td><td>9</td><td>18</td></tr>
<tr><td>HVHA</td><td>23</td><td>92</td><td>23</td><td>6</td></tr>
<tr><td>HVLA</td><td>14</td><td>29</td><td>85</td><td>16</td></tr>
<tr><td>LVLA</td><td>20</td><td>8</td><td>13</td><td>103</td></tr>
</table>

If we compare the results on Cz electrode with those obtained on Fz electrode, it can be seen that the accuracy results related to LA (Low Arousal) trials have become low on Cz electrode. This can be noticed from sensitivity values of HVLA and LVLA classes of emotions in Table 3.5.

Table 3.5: Error analysis on Cz electrode

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	66.7	86.8	62.7	88.7	64.6
HVHA	63.9	86.5	61.3	87.8	62.6
HVLA	59	89.6	65.4	86.8	62
LVLA	71.5	90.7	72	90.5	71.8

The results on Pz electrode are shown in Table 3.6 and Table 3.7.

Table 3.6: The confusion matrix on Pz electrode with single trial ERP attributes

Confusion Matrix on Pz Electrode		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	94	22	7	21
	HVHA	10	98	26	10
	HVLA	14	24	92	14
	LVLA	31	5	10	98

The LVLA results have further lowered if we compare the accuracy results on Fz, Cz and Pz electrodes.

Table 3.7: Error analysis on Pz electrode

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	65.3	87.3	63.1	88.3	64.2
HVHA	68.1	88.2	65.8	89.2	66.9
HVLA	63.9	90	68.1	88.2	65.9
LVLA	68.1	89.6	68.5	89.4	68.3

The Sensitivity and Precision parameters are on the higher side (Table 3.7) as compared to Cz electrode (Table 3.5). Overall four class emotion classification accuracy is higher on Fz (68.2%) followed by Pz (66.3%) and Cz (65.1%). It is worth mentioning over here that though we used same methodology to select features and order of the SVM polynomial classifier but it has been observed that the order and the attributes at which higher classification results along arousal and valence has been determined is not fixed. The number of features varies strongly with subjects (Jenke et al., 2014). Moreover, the emotion classifier is subject dependent. To counter the variability in order and attributes, we decided to fix the attributes and order for subject independent classification. The results obtained are described in the next section.

3.5 Subject Independent Emotion classification based on Single Trial ERPs and Single Trial Difference of ERPs

This section strives to develop an emotion classifier that is not only subject independent but as well uses fixed attributes and polynomial order to classify emotions. EEG ERPs are primarily used for two types of detections

(1) Neurodegenerative diseases

(2) Emotion.

A notable point is that a neurodegenerative disease is more or less a permanent state while emotions are highly transient in nature. For this reason if EEG ERP is employed to detect Neurodegenerative diseases, we may go in for average ERP over a large span of time, extending to over 1000 trials. However for detecting emotions which are more of instantaneous phenomena, single trial ERP tend to produce better results. Further, the studies by Koelstra et al. (2010b), Koelstra et al.(2012), Koelstra and Patras (2013) on single trial EEG signals suggest that single trial signals can be preferred for emotion recognition. A study by Zhang et al. (2013) found evidence that the average amplitude differences in P1, N170, VPP, N3, and P3 are certainly because of single trial ERP variations between experimental conditions. In our study, to reduce the baseline effect, a difference in ERPs has been taken and the subject independent classification has been performed using these attributes (P100-N100, P200-N200, and P300-N300). In this section we have developed and compared two types of emotion classifiers. One is based on six single trial ERPs and the other is based on difference of ERPs. In both the studies, the numbers of trials have been reduced by using simple statistical techniques.

To develop a classifier which is subject independent with fixed attributes and polynomial order, an attribute set of six ERPs [P100 N100 P200 N200 P300 N300] has been used. The SVM polynomial classifier has been fixed with order 3. To reduce data a simple methodology has been used. The ERP data belonging to a particular class of emotion is initially collected for the electrode under observation. The mean and standard deviation of each attribute is then determined. The trial data is chosen if the absolute value of ERP amplitude minus mean (abs (ERP-mean)) is lesser than half of standard deviation. This process has been repeated on the data belonging to all the four classes of emotions. The classification has been performed using 10 fold cross validation on 100 samples with 25 samples belonging to each class of emotion.

In order to offset the effect of day to day variations and the emotion of a subject prior to the data collection (though the subjects were asked to sit with their eyes closed prior to the start of an experiment), the difference of ERPs have been used for classification of emotions. The attributes P100-N100, P200-N200 and P300-N300 are used at polynomial order 3 for classification of emotions. The analysis has been done separately for each electrode i.e. Fz, Cz and Pz are analyzed separately. The mean and standard deviation of three attributes are determined separately for each class. Further, the mean of the standard deviation is determined for each attribute. The samples whose difference from the mean value is lesser than the mean of the standard deviation are selected for building an emotion classifier. To compare the accuracy results obtained on difference of ERPs with absolute ERP results, 100 samples i.e. 25 samples belonging to each class of emotion have been used for testing.

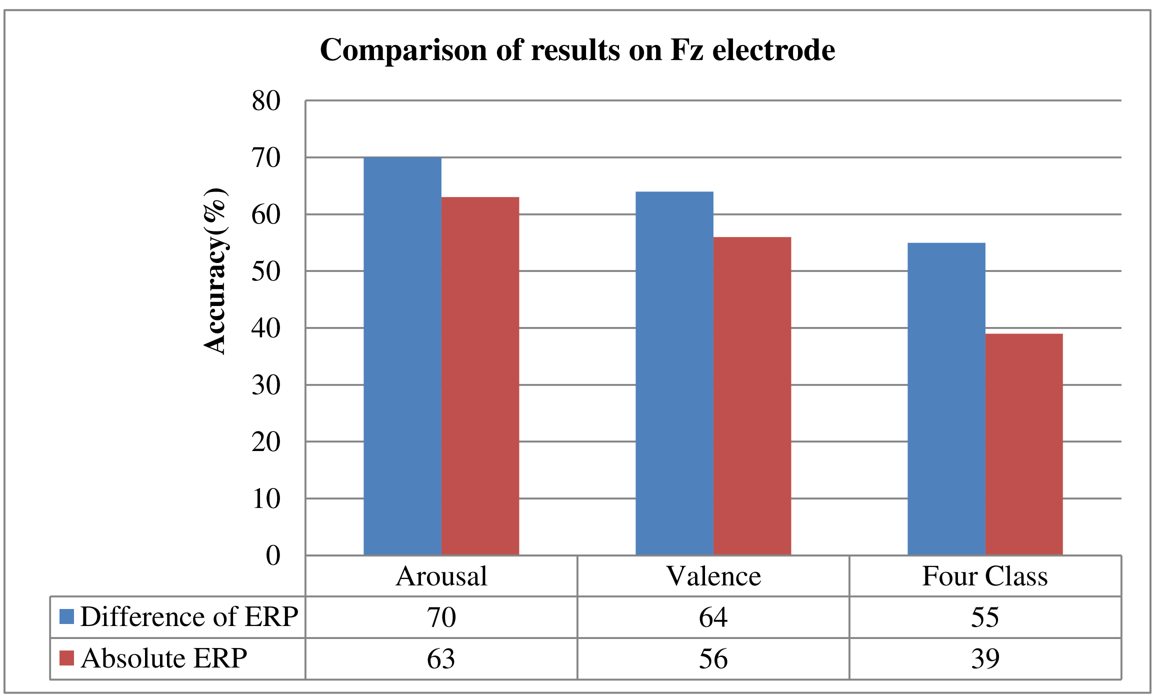


Figure 3.7: Accuracy (%) results on Fz electrode

The subject independent emotion classification results obtained on Fz electrode for both absolute ERP and difference of ERP attributes are shown in Figure 3.7 where as the accuracy results for both subject independent classifiers on Cz and Pz electrodes are shown in Figure 3.8 and Figure 3.9 respectively. It can be seen from Figure 3.7 that difference of ERPs as attributes provide better classification results in terms of arousal, valence and four classes namely LVHA, HVHA, HVLA and LVLA. The results obtained on Cz electrode are shown in Figure 3.8. Comparing the accuracy results on Cz electrode for 100 test trials, it can be seen that the four class emotion classification results are better with difference of ERPs as attributes. A four class emotion classification accuracy of 40% has been obtained. The results are lower as compared to Fz electrode for both the types of attributes.

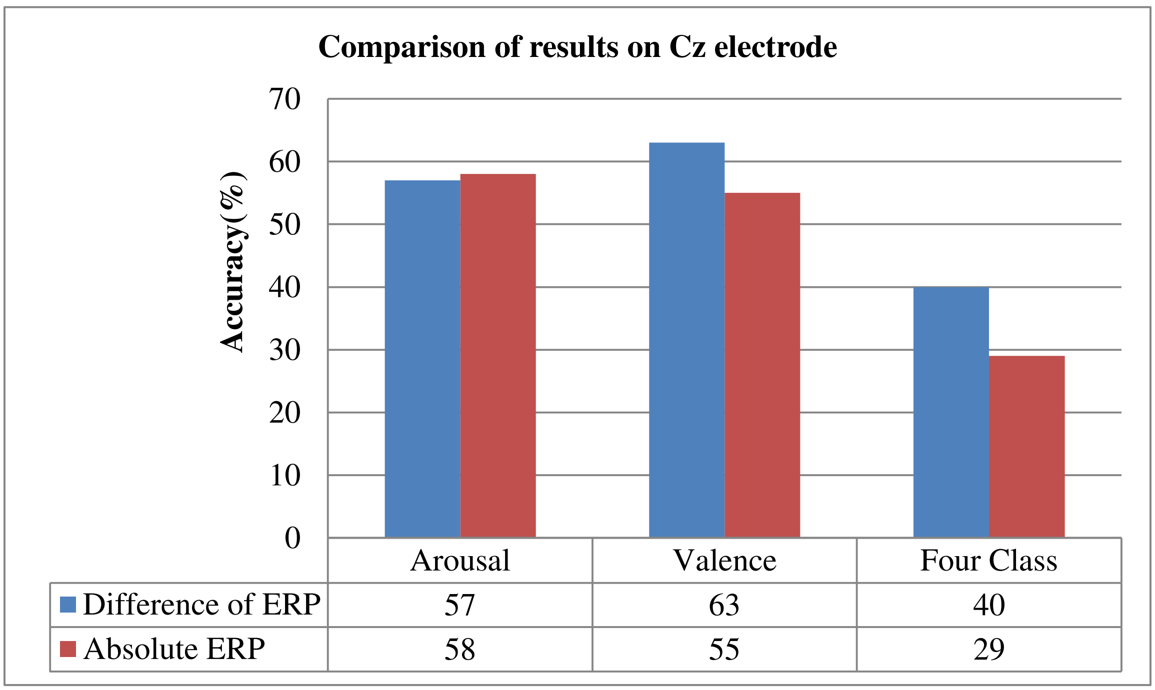


Figure 3.8: Accuracy (%) results on Cz electrode

The Figure 3.9 shows emotion classification results for both attributes on Pz electrode. It can be seen that arousal and valence classification results have improved as compared to Cz electrode. The four class classification accuracy has improved to 50% as compared to 40% on Cz electrode.

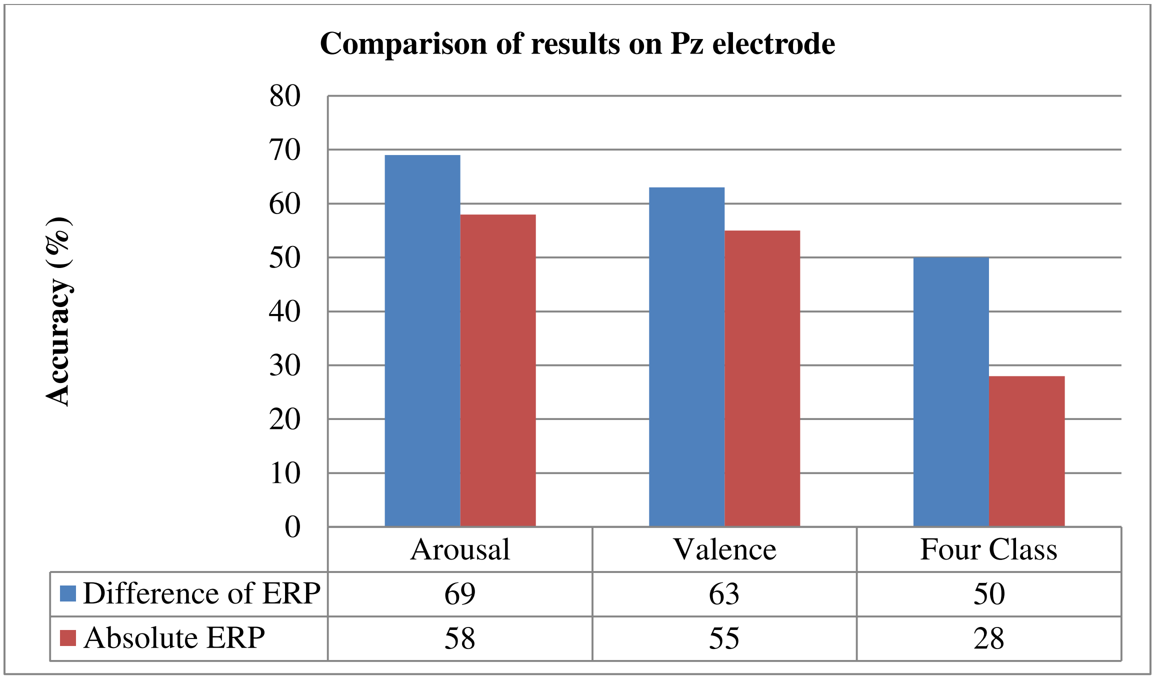


Figure 3.9: Accuracy (%) results on Pz electrode

The valence classification results have been better using difference of ERPs as attributes on all the three electrodes. It is as well worth mentioning over here that the classification results with fixed ERP attributes and SVM polynomial order 3 are lower on any of the electrodes though the results are comparatively better on Fz electrode as compared to Cz and Pz electrodes. The results using absolute ERPs are too low but the classification results using difference of ERP as attributes being better, statistical analysis has been done for these results. The confusion matrix obtained on Fz electrode is shown in Table 3.8, confusion matrix obtained on Cz electrode is shown in Table 3.10 and confusion matrix obtained on Pz electrode is shown in table 3.12. The error analysis for Fz, Cz and Pz electrodes is shown in Table 3.9, Table 3.11 and Table 3.13 respectively.

Table 3.8: Confusion matrix on Fz electrode with difference ERP attributes

Confusion Matrix on Fz Electrode		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	15	0	8	2
	HVHA	3	16	0	6
	HVLA	2	2	13	8
	LVLA	3	8	3	11

Table 3.9: Error analysis on Fz electrode with difference ERP attributes

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	60	89.3	65.2	87	62.5
HVHA	64	86.7	61.5	87.8	62.7
HVLA	52	85.3	54.2	84.2	53.1
LVLA	44	78.6	40.7	80.8	42.3

Table 3.10: Confusion matrix on Cz electrode with difference ERP attributes

Confusion Matrix on Cz Electrode		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	8	3	6	8
	HVHA	2	16	5	2
	HVLA	0	9	12	4
	LVLA	2	11	8	4

Table 3.11: Error analysis on Cz electrode with difference ERP attributes

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	32	94.7	66.6	80.6	43.2
HVHA	64	69.3	41	85	50
HVLA	48	74.7	38.7	81.1	42.9
LVLA	16	81.3	22.2	74.4	18.6

Table 3.12: Confusion matrix on Pz electrode with difference ERP attributes

Confusion Matrix on Pz Electrode		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	15	4	5	1
	HVHA	4	8	7	6
	HVLA	2	5	20	8
	LVLA	3	4	11	7

Table 3.13: Error analysis on Pz electrode with difference ERP attributes

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	60	89.4	62.5	88.3	61.2
HVHA	32	84.7	38.1	80.8	34.8
HVLA	57.1	69.3	46.5	77.6	51.3
LVLA	28	82.3	31.8	79.5	29.8

The error analysis Tables show that the Low Valence Low Arousal class has been the most difficult to classify among the four classes of emotions. Further the F1 score is the best on Fz electrode just like the subject dependent study. The classification results are as well better on Fz electrode in line with the subject dependent study. The classification results using difference of ERPs as attributes are better but needs to be studied using average ERPs as well. We performed the average ERP study as well by dividing the electrodes in four zones viz; all 10 electrodes i.e. full scalp region of our experiment, frontal electrodes, parietal electrodes and central electrodes.

3.6 Results and Discussion

The development of four class subject dependent and subject independent emotion classifiers based on single trial EEG features acquired from central electrodes (Fz, Cz and Pz) have been undertaken. The subject dependent emotion classifiers have been developed for (each of) 24 subjects using single trial ERP features. For each subject three emotion classifiers have been developed. The first classifier is based on single trial ERP features of Fz EEG electrode, the second on single trial ERP features of Cz electrode and the third classifier is based on single trial ERP features obtained from Pz electrode. For each subject dependent emotion classifier (on respective electrode) the testing has been performed on 24 test trials with six test trials belonging to each class of emotion. The best subject dependent emotion classification results have been obtained on Fz electrode with four class emotion accuracy in the range of 58.3 - 83.3% followed by Pz (58.3 - 75%) and Cz (54.2 - 70.8%). The average four class emotion classification accuracy obtained on Fz electrode is 68.2%, on Cz electrode is 65.1% and on Pz electrode is 66.3%. The subject dependent emotion classifiers have low practical utility as the best emotion classification results were obtained for different features and different SVM polynomial order. In other words, we could not zero in on a single attribute set or SVM polynomial order that could be universally used for developing emotion classifier for any subject at a particular electrode.

To counter the drawback of subject dependent emotion classification technique, subject independent emotion classifiers have been developed using single trial ERP features and difference of single trial ERP features. In both the cases, the subject independent emotion classifiers have been developed on Fz electrode, Cz electrode and Pz electrode independently by using SVM polynomial classifier with SVM polynomial order fixed at 3. The testing of a classifier has been performed on 100 test trials with 25 test trials belonging to each class of emotion. The best emotion classification results using single trial ERP features have been obtained at Fz electrode (39%). The accuracy results remain low for this type of feature on all three electrodes (Cz-29%, Pz-28%). This could be due to noise interference and baseline effects.

The low classification results prompted us to use difference of ERPs as features for developing emotion classifier. The three subject independent emotion classifiers have been developed, one using features from Fz electrode, the second classifier is based on the difference of ERP features acquired from Cz electrode and third is based on features of Pz electrode. In all cases SVM polynomial order is fixed at 3 and testing has been performed on 100 test trials with 25 test trials belonging to each class of emotion. The arousal, valence and consequently four class emotion classification results improved on each electrode. The four class emotion classification accuracy of 55% is obtained on Fz electrode, 40% on Cz electrode and 50% on Pz electrode.

Comparing the technique and attributes used to classify emotions with other studies, the advantage of the technique used in our proposed study is that the attributes are obtained directly from the filtered EEG and no other offline processing is required. The extraction of statistical attributes requires offline processing and is a time consuming process. In the proposed study on single trial EEG signals, the extraction of attributes starts with the onset of stimulus.

Comparing results with Koelstra et al. (2012) (DEAP database), arousal was best classified with attributes from EEG signals and valence using physiological signals. In this subject dependent study, average arousal classification accuracy of 62% and average valence classification accuracy of 57.6% was obtained with power spectrum features acquired from EEG. The subject dependent accuracies obtained using single trial ERPs in our proposed study (average arousal classification accuracy on Fz is 80.2% and average valence classification is 81.6%) are better than the accuracies obtained using power spectrum features in the study of Koelstra et al.(2012). However, in a study by Koelstra and Patras (2013) on MAHNOB HCI database, the average classification accuracy along valence axis improved to 71.5% whereas best average arousal accuracy of 67.5% was obtained. The average arousal and valence classification accuracies are above 78% on any electrode in proposed subject dependent study. Our classification results are better than the results proposed by Liu et al. (2013) (average arousal classification accuracy is 73.4% and average valence classification accuracy is 73.57%) and Liu et al. (2014) (average valence classification accuracy is 79.5%). Zheng et al. (2014) used Deep Belief Networks (DBN), DBN-HMM (Hidden Markov Model) and SVM on differential entropy features in five frequency bands of single trial EEG to classify emotions (subject dependent) along the valence axis. The DBN-HMM accuracy lied between 61.4% - 83.3% as compared to 70.8% - 91.7% in our case.

Jatupaiboon et al. (2013) used power spectrum density features in five frequency bands of acquired EEG signals for real time emotion classification. Our classification results 81.6% on Fz, 79.2% on Cz and 82.1% on Pz electrode are better along valence axis as compared to subject dependent average classification of 70.6%. As far as subject independent results are concerned, our results are just better with valence classification of 64% on Fz electrode as compared to 63.7% proposed by Jatupaiboon et al. (2013).

Clearly, the results of our study are comparable with the best of results even though we have used single trial ERP features for analysis. On using difference of ERPs as attributes a better four class emotion classification results have been obtained as compared to absolute ERP attributes. This may be due to the fact that taking difference of ERPs helps in offsetting noise interference effects. Fixing the attributes, order, and designing subject independent classifiers decreases emotional classification accuracy.

3.7 Subject Independent Emotion Classifier based on Average ERP and Difference of Average ERP Attributes

In our study on emotion recognition the single trial ERP analysis has been done only on central electrodes. These electrodes have been used by Frantzidis et al. (2010) for recognition of emotions and best of the four class classification results have been obtained using ERP attributes. For the sake of critical comparison of results and methodology used, the results obtained using average ERP attributes on three electrodes namely Fz, Cz and Pz are described over here.

3.7.1 Feature Extraction and Methodology used

In this section development of a subject independent emotion classifier based on ERP attributes and a subject independent emotion classifier based on difference of ERP attributes are discussed. The data acquisition methodology, filtering operations performed and features used in this study are described in detail in section 3.2 and section 3.3. The evoked continuous EEG signals acquired in response to the stimulus corresponding to four classes of emotions is initially filtered using a notch filter and a band pass filter obtained using IIR low pass and high pass filter. The filtering operations have been performed to remove the power noise of 50 Hz and bring the signal in a usable frequency range of 0.5 Hz to 40 Hz. The EEG signals belonging to a particular class of emotion are then collected as per the SAM ratings and averaging of signals is done. In our case, the stimulus presentation was for 1second, so the EEG signals of length 1second corresponding to each stimulus (of a particular class other than rejected by a subject) are collected and averaged. In this manner we get one EEG signal per electrode for a particular class of emotion. The 12 ERP attributes (6 ERPs and 6 corresponding latencies) namely P100, N100, PT100, NT100, P200, N200, PT200, NT200, P300, N300, PT300 and NT 300 as specified in Table 3.1 are then extracted from EEG. For emotion classifier based on ERP attributes, these 12 ERP attributes have been used. In the second analysis i.e. development of an emotion classifier based on difference of ERP attributes, we used differential ERP attributes such as (P100-N100), (P200-N200), (P300-N300) and the latencies PT100, NT100, PT200, PT300 and NT300 as attributes. The acquisition methodology is described in Figure 3.10.

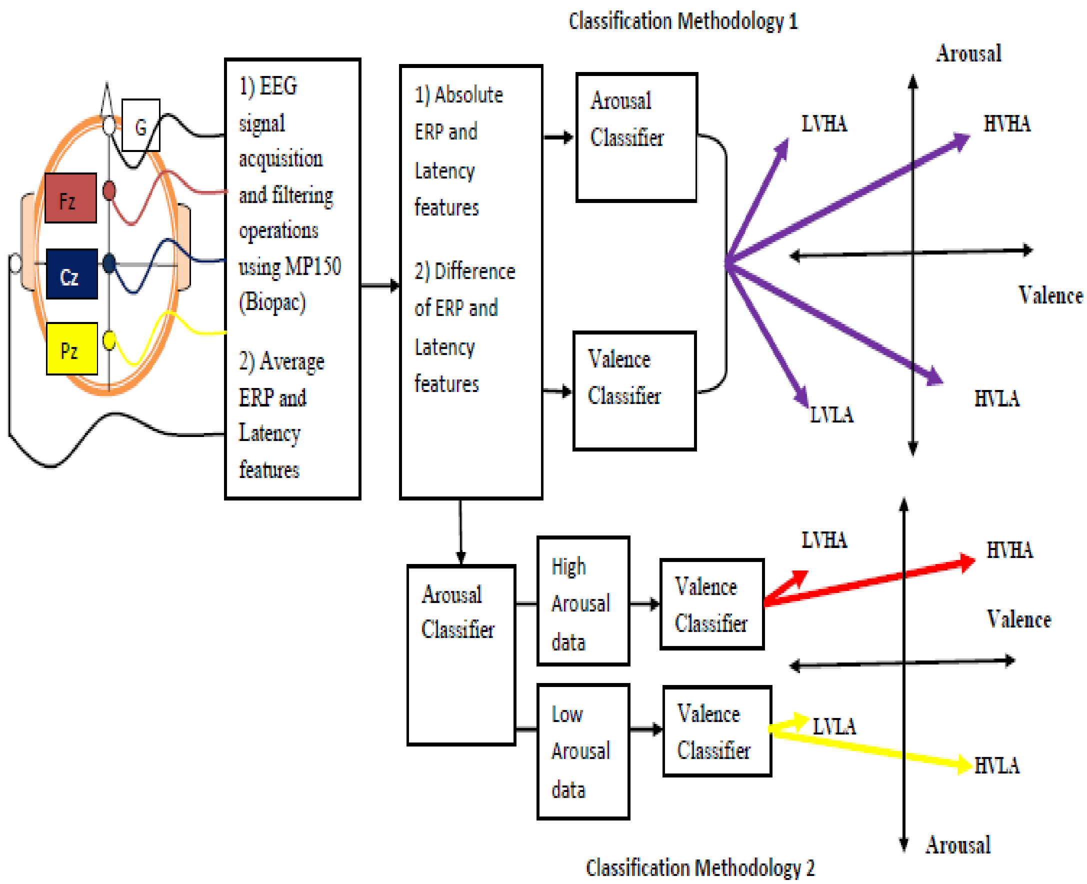


Figure 3.10: The methodology used in classification of emotions with average ERP attributes

3.7.2 Results

For test analysis of developed classifier (subject independent), the test data consists of a total of 56 instances with 14 belonging to each class of emotion. The test set has been selected keeping in view the number of test samples used in Frantzidis et al. (2010). The use of SVM with polynomial kernel in the proposed study is influenced by its successful usage in other studies (Sourina and Liu, 2014; Petrantonakis and Hadjileontiadis, 2010a). The best ‘C’ value has been determined after 10 fold cross-validation on the training set on the best SVM polynomial order. The SVM polynomial classifier in Matlab has then been tested on the test set which is not a part of the training set on which cross-validation has been performed.

The emotion classification using SVM polynomial has been performed in two ways on absolute as well as differential of average ERPs. One is by using two separate classifiers to classify emotions along two independent axes i.e. arousal (low arousal and high arousal) and valence (low valence and high valence). The combination of the output of these two classifiers enabled the classification into four classes of emotions. The classification technique has been shown as classification methodology 1 in Figure 3.10. In a second procedure we adopted, we first classified emotions along arousal axis into low arousal and high arousal. The valence classification was then performed on low arousal and high arousal data using two separate classifiers. Thus the classification requires three separate classifiers shown as classification methodology 2 in Figure 3.10.

The feature selection technique at a particular order of SVM polynomial has been performed in a manner similar to feature selection technique used in subject dependent studies involving single trial EEG signals. To select features instead of using WEKA as was done by Frantzidis et al. (2010), we programmed in Matlab. On a particular order of SVM polynomial classifier all the features (full ERP set or difference of ERPs) are initially selected for training a classifier. Accuracy of classification (arousal or valence) is determined. New attribute set is selected by removing one of the attributes in preset order. The classifier is again trained and tested. If the accuracy using new attribute set is more than the previous one, new attribute set is retained and the previous one is ignored. A new attribute set is now generated by removing or retaining a new attribute and the accuracy using a new attribute set is now compared with previous one. This process of selecting features (and SVM polynomial order) is continued till the classification accuracy does not increase further. For example, in development of subject independent emotion classifier based on absolute ERPs, the process of feature selection starts by taking all 12 features as an attribute set for training a classifier on the SVM polynomial order 3(say) and the test accuracy is determined. The features are reduced one by one in a preset order with each removal retained if it resulted in enhanced or sustained accuracy. For example, on removing P100 if accuracy increases or remains same, further removal is carried out without P100. On other hand if removal of P100 decreases accuracy, further reduction is done with P100 as part of feature set. This feature reduction is done by systematic reduction in features made in pre-determined order. The same procedure is repeated for the next order of SVM polynomial classifier. The lowest order providing highest accuracy has been chosen in this proposed study. Similar operations have been performed using difference of ERPs and six latencies namely P100-N100, P200-N200, P300-N300, PT100, NT100, PT200, NT200, PT300, NT300. The results obtained on average ERP parameters and difference of ERP attributes for three electrodes namely Fz, Cz and Pz using orthogonal property of arousal and valence domains i.e. after using classification methodology 1are described in Table 3.14.

Table 3.14: Emotion classification results on average ERP and difference of average ERP attributes using two classifiers

	Emotion Classification Results (%)						
	Arousal	Valence	LVHA	HVHA	HVLA	LVLA	Four Class Accuracy
Average ERP and Latencies	82.1	80.3	71.4	85.7	71.4	64.3	73.2
Correctly Classified Instances (CCI)	46	45	10	12	10	9	41
Order	3	3	3	3	3	3	3
Differential ERP and Absolute Latencies	82.1	85.7	85.7	71.4	71.4	71.4	75
Correctly Classified Instances (CCI)	46	48	12	10	10	10	42
Order	3	3	3	3	3	3	3

The test sample consisted of 56 instances with 14 instances belonging to each class of emotion. When classifying with average ERP and corresponding latencies, 46 samples have been correctly classified along arousal axis and 45 along valence axis. The four class classification accuracy is more than 73%. With differential ERP attributes, the four class classification accuracy increased to 75%. The classification accuracy for each class of emotion remained above 71% and the results show improvement over average ERP.

As far as classification results using classification methodology 2 are concerned, the Table 3.15 shows some improvement over the results.

Table 3.15: Emotion classification results on average ERP and difference of average ERP attributes using three classifiers

	Emotion Classification Results (%)									
	Arousal	Low Arousal		High Arousal		LVHA	HVHA	HVLA	LVLA	Four Class Accuracy
		L. V.	H.V	L.V.	H.V.					
Average ERP and Latencies	82.1	85.7	92.8	78.6	92.8	78.6	71.4	78.6	71.4	75
Correctly Classified Instances (CCI)	46	12	13	11	13	11	12	11	10	42
Order	3	5		3		(3,3)		(3,5)		Arousal at 3, Valence at 5 and 3
Differential ERP and Absolute Latencies	82.1	92.8	85.7	92.8	92.8	85.7	78.6	71.4	71.4	76.8
Correctly Classified Instances (CCI)	46	13	12	13	13	12	11	10	10	43
Order	3	3		4		(3,4)		(3,3)		Arousal at 3, Valence at 3 and 4

As Table 3.15 shows, 46 out of 56 instances have been correctly classified along the arousal axis i.e arousal has been classified with 82.1% accuracy on both type of attributes namely average ERP and latency attributes as well as differential average ERP attributes and latencies. This arousal classifier is a first of three classifiers used for classification of emotions. The classification methodology is described in Figure 3.11. The second classifier classified low arousal data into low valence and high valence classes. For low arousal data, 25 samples have been classified correctly into low valence and high valence categories with an accuracy of 89.2%. For high arousal data, 24 samples have been correctly classified along the valence axis at an accuracy of 85.7%. A four class classification accuracy of 75% has been obtained using average ERP attributes whereas an accuracy of 76.8% has been obtained when using differential average ERP attributes.

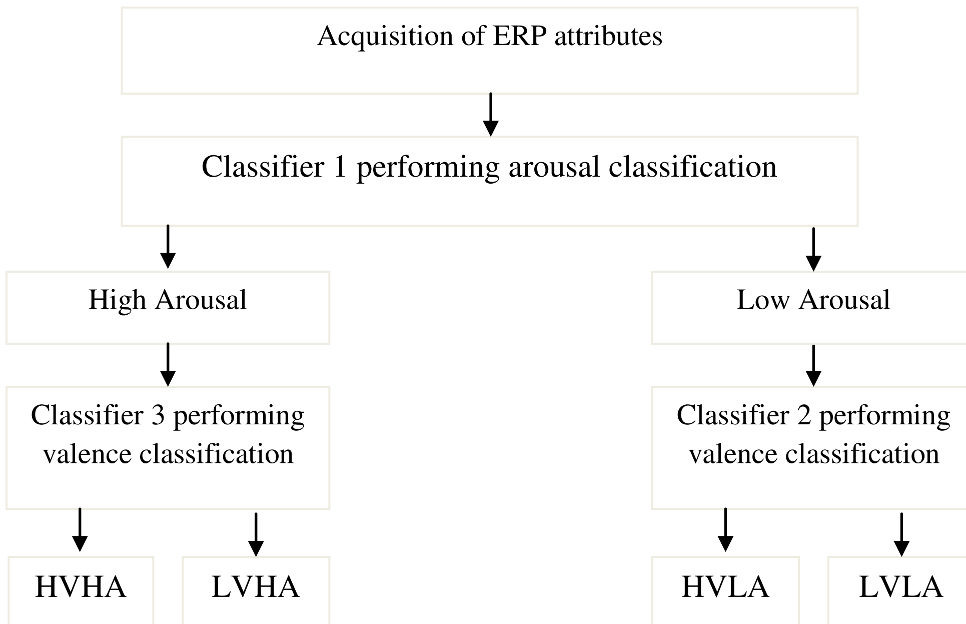


Figure 3.11: The classification process using 3 classifiers used for acquiring results in Table 3.15

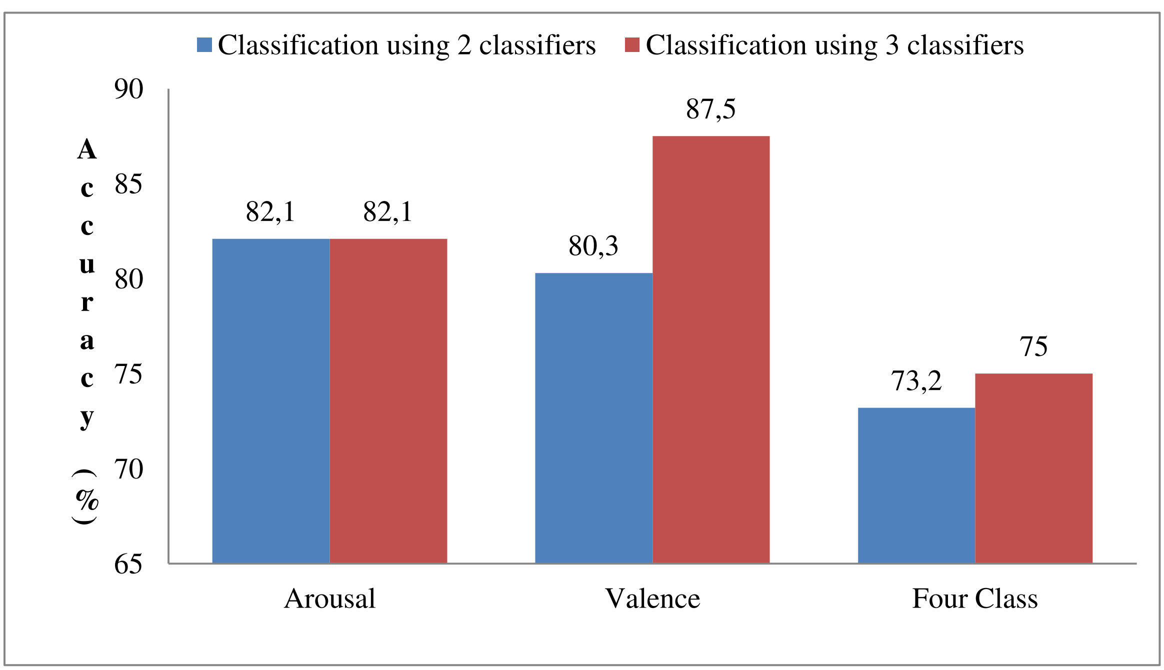


Figure 3.12: Results using average ERP and latency features

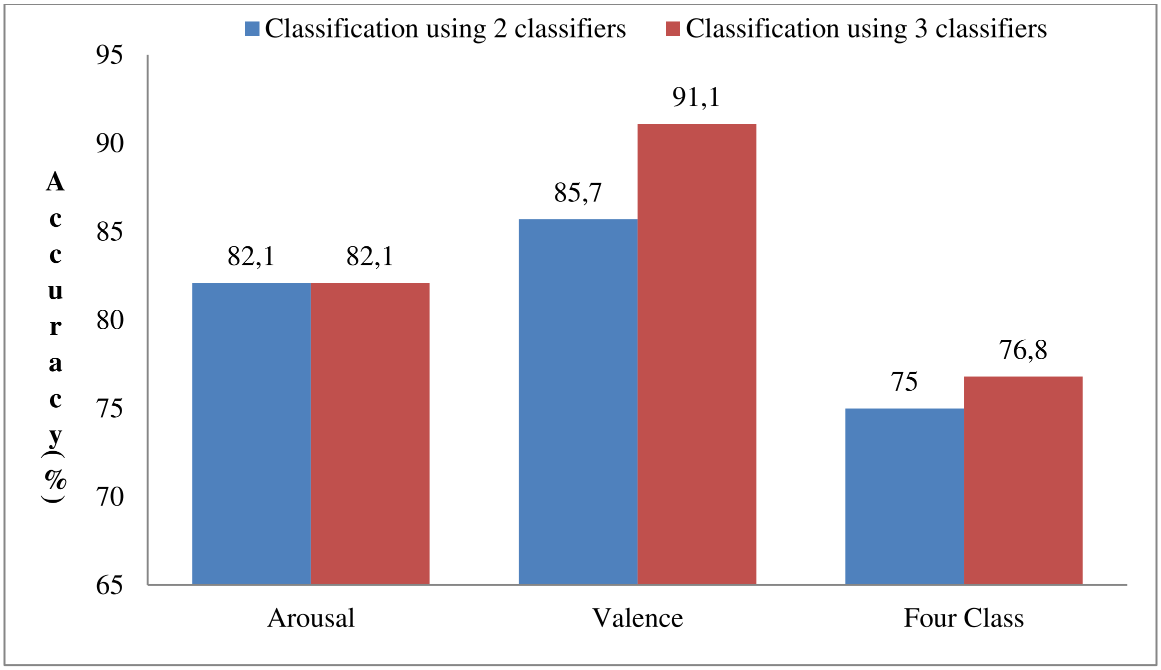
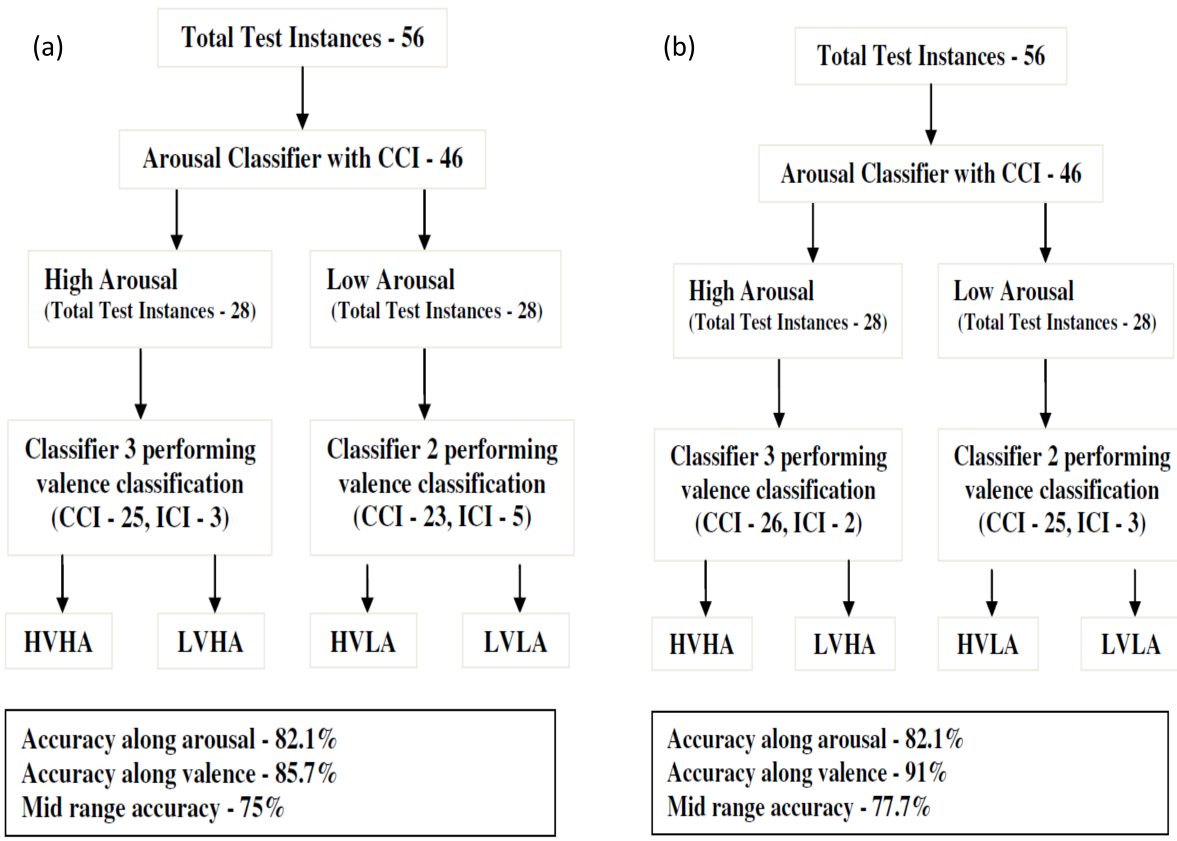


Figure 3.13: Results using difference of average ERP and latency features

If we compare Figure 3.12 and Figure 3.13, then it can be seen that the use of differential average ERP attributes improves the classification results just by one sample. Further using a three classifier technique does not improve the results to a large extent even though we have obtained classification results better than Frantzidis et al. (2010). It has been found that the features selected for classification of valence for both low arousal and high arousal data remains the same. This is in line with the fact that arousal and valence are considered orthogonal emotions. The attribute on which valence is classified with higher accuracy would produce the same result for low arousal or high arousal results. To change the results by changing the order of a SVM polynomial classifier is not a good idea. So the results in other chapters have been presented using a two classifier technique only. Further, we have analyzed electrodes along the central line only. Higher results using average ERP attributes and differential attributes makes it necessary to try other combination of electrodes especially frontal electrodes. The results have been analyzed in Chapter 4.

3.7.3 Discussion

When we started with our experiments in 2013, the study by Frantzidis et al. (2010) was among the prominent studies on emotion classification using ERP demonstrating high emotion classification results. Our experimental protocol has been a lot influenced by this study. So it becomes necessary to compare the obtained results with the existing study as we feel that using a three classifier method is not fundamentally correct if classification is done considering orthogonal relationship between arousal and valence. The Figure 3.14 illustrates the comparison process.



*CCI- Correctly Classified Instances, ICI-Incorrectly Classified Instances

Figure 3.14: (a) Results obtained by Frantzidis et al. (2010) (b) Results obtained using difference of average ERPs on central electrodes in this study

In a first step, Frantzidis et al. (2010) obtained a classification accuracy of 82.1% along arousal axis i.e. the number of Incorrect Classified Instances (ICI) were 10 (i.e. Correctly

Classified Instances (CCI) were 46) when classifying data (Total Instances-56) into low arousal and high arousal classes. In a second step, Frantzidis et al. (2010) classified low arousal data (Total Instances-28) into low valence and high valence at an accuracy of 82.1% (CCI-23, ICI-5). For high arousal data, the low valence and high valence classifications were obtained at an accuracy of 89.2% (CCI-25, ICI-3).

For comparison of four class emotion classification results, further elaboration of results is required. The first classifier (arousal classifier) correctly classified 46 out of 56 instances. So on classifying arousal data into valence, a total of 10 incorrectly classified instances will always be there. It becomes pertinent to mention here that the total number of errors in four class emotion classification depends upon which instances have been wrongly classified by the second and third classifiers. If the instance incorrectly classified by second or third classifier is other than the instances incorrectly classified by the first classifier, it will add to an error. All the misclassifications of second and third classifiers being those instances which have been wrongly classified by the first classifier (arousal classifier in this case) will result in maximum possible four class emotion accuracy. On the contrary if the instances classified by both the valence classifiers are different from those instances wrongly classified by arousal classifier, the ICIs of all the three classifiers will add up and will result in minimum four class emotion accuracy. Thus as shown in Figure 3.14 (a) representing results of Frantzidis et al. (2010), the incorrectly classified instances are in the range of 10-18 resulting in a four class emotion accuracy in the range of 67.9 - 82.1% i.e. CCI is in range of 38-46. The mid range accuracy thus comes out to be 75% in case of Frantzidis et al. (2010). Comparing the results on differential average ERP attributes (Figure 3.14 (b)), our results are better. For valence classification of low arousal data, 25 samples have been correctly classified as compared to 23 by Frantzidis et al. (2010). Similarly, when classifying high arousal data along valence axis, 26 instances, one more than that reported by Frantzidis et al. (2010) have been classified correctly i.e. an accuracy of 92.8% has been obtained as compared to the existing 89.2%. The CCI lie in the range of 41 - 46 resulting in four class emotion accuracy in the range of 73.2 - 82.1%. The mid range accuracy is 77.7%. The results show an improvement over the existing study on average ERPs. To make a better comparison, the emotion classification on other combination of electrodes needs to be analyzed.

3.8 Summary

This Chapter shows the use of ERP attributes for development of subject dependent as well as subject independent emotion classifiers. The three electrodes namely Fz, Cz and Pz have been chosen as per the results and findings of different studies. The analysis on these electrodes has been done in number of ways. Some of the prominent findings are summarized below.

1) The subject dependent emotion classifier (on each electrode i.e Fz, Cz and Pz) has been developed for 24 subjects using single trial ERP features. The best emotion classification results have been obtained on Fz electrode. The average arousal classification accuracy obtained on Fz electrode is 80.2%, average valence classification is 81.6% and average four class classification is 68.2%. The average four class emotion classification accuracy obtained on Cz electrode is 65.1% and on Pz electrode is 66.3%. However for each subject dependent emotion classifier the features selected from among the 12 ERP attributes and SVM polynomial order was different. This practically limits the use of subject dependent emotion classifiers.
2) The subject independent emotion classifiers based on single trial ERPs have been developed (on each electrode i.e Fz, Cz and Pz) as well. The four class emotion classification accuracy on Fz electrode is 39%, on Cz electrode is 29% and on Pz electrode is 28%. Better results have been obtained when difference of single trial ERPs are used for subject independent emotion classification. The four class subject independent emotion classification accuracy on Fz electrode is 55%, on Cz electrode is 40% and on Pz electrode is 50%.
3) The subject independent emotion classifiers have also been developed with average of ERPs as attributes and difference of average ERP attributes. Using two classifiers technique, a four class emotion classification accuracy of 73.2% has been obtained with average ERPs as attributes. With difference of average ERP attributes a four class classification accuracy of 75% has been obtained. However using three classifiers a four class emotion classification accuracy using average

ERP attributes is 75% and with difference of average ERP attributes is 76.8%. The results obtained are better than previous study of Frantzidis et al. (2010).

CHAPTER-4

OPTIMAL SELECTION OF EEG ELECTRODES FOR EMOTION RECOGNITION

4.1 Introduction

The classification results obtained on central electrodes prompted us to analyze different combinations of electrodes placed in different regions of human brain. We described the EEG data acquisition methodology and the hardware including EEG cap and bio amplifiers we used in our experiments in Chapter 2. We have used 10 EEG electrodes for data acquisition from 24 human subjects. This Chapter includes the development and analysis of the subject independent emotion classifiers based on average ERP attributes and difference of average ERP attributes. The classifiers have been developed by using features from different combination of electrodes viz; all 10 electrodes, frontal electrodes, parietal electrodes and all electrodes except central electrodes. For example, the classifier developed on all 10 electrodes contains features from all electrodes, namely, Fp1, Fp2, F3, F4, F8, Fz, Cz, Pz, P3 and P4, the classifier developed on frontal region contains features from frontal electrodes Fp1, Fp2, F3, F4, F8 and Fz, the classifier based on parietal electrodes uses features from EEG electrodes Pz, P3 and P4 and classifier developed on all electrodes except central electrodes uses features from seven of 10 EEG electrodes (except Fz, Cz and Pz) as shown in Figure 4.1. The SVM polynomial classifier has been used for classification of emotions into four classes namely LVHA, HVHA, HVLA and LVLA. The feature reduction, cost factor (best C) determination, cross-validation and methodology used for selection of order of SVM polynomial classifier between 3 to 6 remains the same as described in section 3.7.2 of Chapter 3. Apart from this, the emotion classifiers along arousal and valence have as well been developed by setting the order of SVM polynomial classifier at 3. Thus for each combination of electrodes, three subject independent emotion classifiers have been developed. One is the emotion classifier based on average ERPs with SVM polynomial order between 3-6 as in Frantzidis et al. (2010), the second emotion classifier is based on average ERP features with SVM polynomial order fixed at 3. The third emotion classifier is based on difference of average ERP features with SVM polynomial order between 3-6 and the fourth classifier is based on difference of average ERP features with SVM polynomial order fixed at 3. In all cases we have considered self assessment as gold standard for training and testing of four class emotion classifier. The test sample for any trained classifier consists of 100 instances with 25 instances belonging to each class of emotion viz; LVHA, HVHA, HVLA and LVLA.

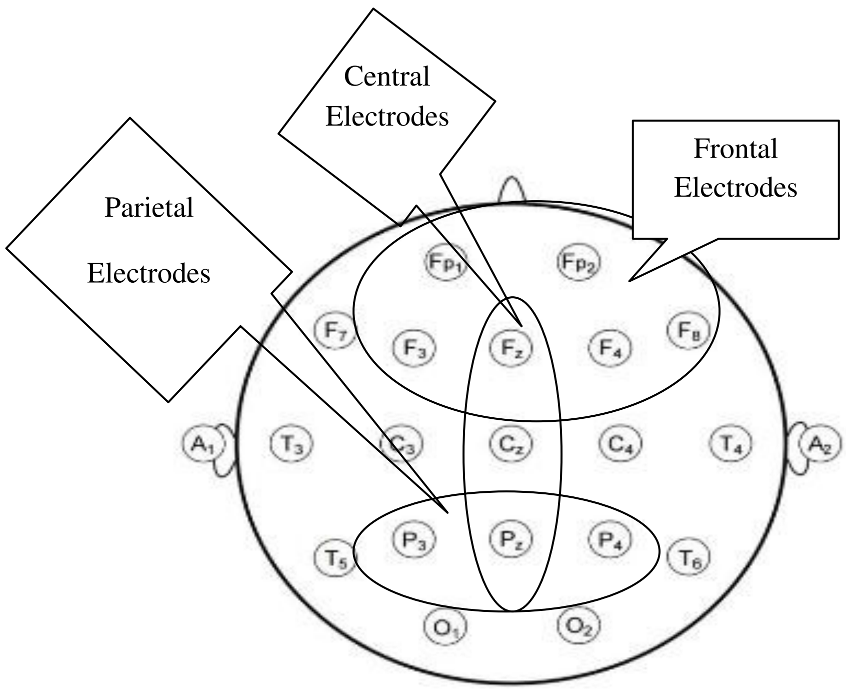


Figure 4.1: The ten electrodes and various combinations used for emotion analysis

4.2 Emotion Classification on 10 Electrodes

The emotion classification results obtained on 10 electrodes for absolute and differential ERP features by using SVM polynomial classifier are described in this section. When using all 10 electrodes comprising various frontal, central and parietal electrodes (namely Fp1, Fp2, F3, F4, F8, Fz, Cz, Pz, P3 and P4) the arousal classification accuracy of 86% at SVM polynomial order 3 has been obtained while valence classification is 85% at SVM polynomial order 6. The four class emotion classification is 75% as shown in Table 4.1.

Table 4.1: The four class confusion matrix obtained for all 10 electrodes using absolute ERPs

Confusion Matrix on all 10 Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	18	4	1	2
	HVHA	0	18	6	1
	HVLA	2	0	19	4
	LVLA	2	0	3	20

Table 4.2: The error analysis on all 10 electrodes for results in Table 4.1

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	72.0	94.7	81.8	91.0	76.6
HVHA	72.0	94.7	81.8	91.0	76.6
HVLA	76.0	86.7	65.5	91.5	70.4
LVLA	80.0	90.7	74.1	93.2	76.9

The Table 4.2 shows sensitivity, specificity, precision, negative predictive value and F1 score obtained for results on all 10 electrodes. The error analysis parameters are described in percentage. On fixing the SVM polynomial order at 3 for classification of emotions along arousal and valence axis, arousal classification accuracy of 86% and valence classification accuracy of 81% has been obtained. This gives four class emotion classification results of 71%. The confusion matrix and error analysis is shown in Table 4.3 and Table 4.4 respectively.

Table 4.3: The confusion matrix on all 10 electrodes with SVM polynomial order set at 3 when using absolute average ERPs as attributes

Confusion Matrix on all 10 Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	19	3	0	3
	HVHA	2	16	5	2
	HVLA	1	1	18	5
	LVLA	1	1	5	18

Table 4.4: The error analysis on all 10 electrodes for results in Table 4.3

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	76.0	94.7	82.6	92.2	79.2
HVHA	64.0	93.3	76.2	88.6	69.6
HVLA	72.0	86.7	64.3	90.3	67.9
LVLA	72.0	86.7	64.3	90.3	67.9

The decrease in valence classification accuracy decreases the sensitivity parameter of each class. The F1 score is lower in Table 4.4 as compared to Table 4.2.

When using difference of average ERPs as attributes, a four class emotion classification accuracy of 72% has been obtained with arousal classification accuracy of 85% on order 4 and valence classification of 83% on order 6. The Table 4.5 shows the confusion matrix obtained when using differential average ERP attributes for emotion classification. The Table 4.6 shows the error analysis for differential average ERP attributes.

Table 4.5: The four class confusion matrix obtained for all 10 electrodes using differential average ERPs

Confusion Matrix on all 10 Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	18	2	3	2
	HVHA	3	19	2	1
	HVLA	0	1	20	4
	LVLA	6	0	4	15

Table 4.6: The error analysis on all 10 electrodes for results in Table 4.5

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	72.0	88.0	66.7	90.4	69.2
HVHA	76.0	96.0	86.4	92.3	80.9
HVLA	80.0	88.0	69.0	93.0	74.1
LVLA	60.0	90.7	68.2	87.2	63.8

When the SVM polynomial is fixed at order 3, the arousal classification accuracy obtained is 76%, valence classification accuracy is 81% giving four class classification accuracy of 66%. The confusion matrix and error analysis is shown in Table 4.7 and Table 4.8 respectively.

Table 4.7: The four class confusion matrix obtained for all 10 electrodes using differential average ERPs with SVM polynomial order set at 3

Confusion Matrix on all 10 Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	18	2	2	3
	HVHA	4	15	2	4
	HVLA	1	3	19	2
	LVLA	7	2	2	14

Table 4.8: The error analysis on all 10 electrodes for results in Table 4.7

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	72.0	84.0	60.0	90.0	65.5
HVHA	60.0	90.7	68.2	87.2	63.8
HVLA	76.0	92.0	76.0	92.0	76.0
LVLA	56.0	88.0	60.9	85.7	58.3

4.3 Emotion Classification on Frontal Electrodes

The best classification results have been obtained when using all frontal EEG electrodes viz; Fp1, Fp2, F3, F4, F8 and Fz for classification of emotions. The two class classification of emotions along arousal axis could be done with an accuracy of 88% (at SVM polynomial order 6) whereas along valence axis, a classification accuracy of 94% has been obtained at SVM polynomial order 4. The high two class classification results ultimately yielded the best four class classification result of 83%. This is the best result obtained using average ERPs as attributes on any electrode combination we analyzed in this paper. The results are even better than those obtained by using Frantzidis et al. (2010) using average ERPs. The results are shown in Table 4.9 and Table 4.10.

Table 4.9: The four class confusion matrix obtained for frontal electrodes using absolute ERPs

Confusion Matrix on Frontal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	22	2	0	1
	HVHA	1	23	1	0
	HVLA	1	3	21	0
	LVLA	6	0	2	17

Table 4.10: The error analysis on frontal electrodes for results in Table 4.9

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	88.0	89.3	73.3	95.7	80.0
HVHA	92.0	93.3	82.1	97.2	86.8
HVLA	84.0	96.0	87.5	94.7	85.7
LVLA	68.0	98.7	94.4	90.2	79.1

The analysis has also been performed with SVM polynomial order fixed. With the SVM polynomial order fixed at 3, the emotion classification along arousal axis is 79% and along valence axis is 81%. A four class classification accuracy of 67% has been obtained. The confusion matrix and individual class classification accuracy results are shown in Table 4.11 and Table 4.12.

Table 4.11: The confusion matrix on frontal electrodes using absolute average ERPs with SVM polynomial order set at 3

Confusion Matrix on Frontal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	20	2	1	2
	HVHA	5	16	4	0
	HVLA	3	4	15	3
	LVLA	4	3	2	16

Table 4.12: The error analysis on frontal electrodes for results in Table 4.11

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	80.0	84.0	62.5	92.6	70.2
HVHA	64.0	88.0	64.0	88.0	64.0
HVLA	60.0	90.7	68.2	87.2	63.8
LVLA	64.0	93.3	76.2	88.6	69.6

The high classification results have as well been obtained on frontal electrodes when using differential average ERP attributes. The results are shown in Table 4.13 and Table 4.14.

Table 4.13: The confusion matrix on frontal electrodes using differential average ERPs

Confusion Matrix on Frontal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	20	1	0	4
	HVHA	1	19	5	0
	HVLA	1	2	19	3
	LVLA	2	0	4	19

Table 4.14: The error analysis on frontal electrodes for results in Table 4.13

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	80.0	94.7	83.3	93.4	81.6
HVHA	76.0	96.0	86.4	92.3	80.9
HVLA	76.0	88.0	67.9	91.7	71.7
LVLA	76.0	90.7	73.1	91.9	74.5

The four class emotion classification accuracy of 77% has been obtained with arousal classification accuracy of 86% and valence classification accuracy of 90% at SVM polynomial orders 3 and 6 respectively. The individual classification accuracy of each class remains above 75% as shown in Table 4.14.

When the SVM polynomial order is fixed at 3 for classifying emotions along arousal axis and valence domain, a four class classification accuracy of 74% has been obtained with arousal classification of 86% and valence classification of 85%. The results are shown in Table 4.15 and Table 4.16

Table 4.15: The confusion matrix on frontal electrodes using differential average ERPs with SVM polynomial order set at 3

Confusion Matrix on Frontal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	21	0	2	2
	HVHA	2	18	5	0
	HVLA	0	3	18	4
	LVLA	1	1	6	17

Table 4.16: The error analysis on frontal electrodes for results in Table 4.15

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	84.0	96.0	87.5	94.7	85.7
HVHA	72.0	94.7	81.8	91.0	76.6
HVLA	72.0	82.7	58.1	89.9	64.3
LVLA	68.0	92.0	73.9	89.6	70.8

It becomes pertinent to mention here that higher classification results have been obtained on frontal electrodes even when SVM polynomial order is fixed at default value 3.

4.4 Emotion Classification on Parietal Electrodes

The analysis has been done on three parietal electrodes namely P3, P4 and Pz. With average ERP as attributes, the emotion classification accuracy of 83% has been obtained along arousal axis and 86% along valence axis at orders 6 and 3 respectively. The four class classification accuracy lies at 72 %. The results are shown in Table 4.17 and Table 4.18.

Table 4.17: The confusion matrix on parietal electrodes using absolute average ERPs

Confusion Matrix on Parietal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	15	2	0	8
	HVHA	5	20	0	0
	HVLA	3	4	14	4
	LVLA	2	0	0	23

Table 4.18: The error analysis on parietal electrodes for results in Table 4.17

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	60.0	86.7	60.0	86.7	60.0
HVHA	80.0	92.0	76.9	93.2	78.4
HVLA	56.0	100.0	100.0	87.2	71.8
LVLA	92.0	84.0	65.7	96.9	76.7

The results obtained with SVM polynomial order set at 3 on absolute average ERP attributes are shown in Table 4.19 and Table 4.20.

Table 4.19: The confusion matrix on parietal electrodes using absolute average ERPs with SVM polynomial order set at 3

Confusion Matrix on Parietal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	16	0	2	7
	HVHA	5	20	0	0
	HVLA	2	6	14	3
	LVLA	4	0	2	19

Table 4.20: The error analysis on parietal electrodes for results in Table 4.19

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	64.0	85.3	59.3	87.7	61.5
HVHA	80.0	92.0	76.9	93.2	78.4
HVLA	56.0	94.7	77.8	86.6	65.1
LVLA	76.0	86.7	65.5	91.5	70.4

A four class emotion classification accuracy of 69% has been obtained as shown in Table 4.19.

When using differential average ERP attributes a four class emotion accuracy of 71% has been obtained with arousal classification accuracy of 82% (SVM polynomial order 4) and valence classification accuracy of 85% (SVM polynomial order 4). The confusion matrix and error analysis is shown in Table 4.21 and Table 4.22 respectively.

Table 4.21: The confusion matrix on parietal electrodes using differential average ERPs

Confusion Matrix on Parietal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	15	2	0	8
	HVHA	5	20	0	0
	HVLA	3	4	14	4
	LVLA	2	1	0	22

Table 4.22: The error analysis on parietal electrodes for results in Table 4.21

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	60	86.7	60	86.7	60
HVHA	80	90.7	74.1	93.2	76.9
HVLA	56	100	100	87.2	71.8
LVLA	88	84	64.7	95.5	74.6

With SVM polynomial order fixed at 3, four class emotion classification accuracy improved by one sample to 70% as compared to accuracy obtained using differential average ERP attributes when polynomial order is fixed. The results are shown in Table 4.23 and Table 4.24.

Table 4.23: The confusion matrix on parietal electrodes using differential average ERPs with SVM polynomial order set at 3

Confusion Matrix on Parietal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	17	0	2	6
	HVHA	5	20	0	0
	HVLA	2	6	14	3
	LVLA	4	0	2	19

Table 4.24: The error analysis on parietal electrodes for results in Table 4.23

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	68.0	85.3	60.7	88.9	64.2
HVHA	80.0	92.0	76.9	93.2	78.4
HVLA	56.0	94.7	77.8	86.6	65.1
LVLA	76.0	88.0	67.9	91.7	71.7

Since, it can be seen from the Tables 4.1 - 4.24 that the best accuracy results have been obtained on frontal electrodes followed by parietal electrodes, we decided to analyze the results on seven electrodes (frontal and parietal electrodes) namely Fp1, Fp2, F3, F4, F8, P3 and P4.

4.5 Emotion Classification on Frontal and Parietal Electrodes

The classification of emotions has been done on both average and differential average ERPs considering both cases when the best order of SVM polynomial classifier is determined between 3 - 6 and when fixed at order 3. The results are shown in Table 4.25 to Table 4.28.

Table 4.25: The confusion matrix on frontal and parietal electrodes using absolute average ERPs

Confusion Matrix on Frontal and Parietal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	16	6	0	3
	HVHA	3	21	0	1
	HVLA	0	5	19	1
	LVLA	5	1	0	19

Table 4.26: The error analysis for results in Table 4.25

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	64.0	89.3	66.7	88.2	65.3
HVHA	84.0	84.0	63.6	94.0	72.4
HVLA	76.0	100.0	100.0	92.6	86.4
LVLA	76.0	93.3	79.2	92.1	77.6

On absolute ERPs as attributes, a four class emotion classification accuracy of 75% has been obtained with arousal classification accuracy of 85% (order 6) and valence classification accuracy of 88% (order 6).

When the order is fixed at 3, the emotions could be classified along arousal axis with accuracy of 82% and along valence axis with an accuracy of 85%. The four class emotion classification accuracy of 71% has been obtained. The results are shown in Table 4.27 and Table 4.28.

Table 4.27: The confusion matrix on frontal and parietal electrodes using absolute average ERPs with SVM polynomial order set at 3

Confusion Matrix on Frontal and Parietal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	16	7	0	2
	HVHA	0	18	5	2
	HVLA	1	3	20	1
	LVLA	4	1	3	17

Table 4.28: The error analysis for results in Table 4.27

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	64.0	93.3	76.2	88.6	69.6
HVHA	72.0	85.3	62.1	90.1	66.7
HVLA	80.0	89.3	71.4	93.1	75.5
LVLA	68.0	93.3	77.3	89.7	72.3

When classification is done using differential average ERP attributes, a four class classification accuracy of 74% has been obtained with arousal classification of 85% at SVM polynomial order 5 and valence classification of 85% at SVM polynomial order 6. The results are shown in Table 4.29. The error analysis is shown in Table 4.30.

Table 4.29: The confusion matrix on frontal and parietal electrodes using differential average ERPs

Confusion Matrix on Frontal and Parietal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	17	4	3	1
	HVHA	3	19	3	0
	HVLA	1	1	23	0
	LVLA	6	0	4	15

Table 4.30: The error analysis for results in Table 4.29

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	68.0	86.7	63.0	89.0	65.4
HVHA	76.0	93.3	79.2	92.1	77.6
HVLA	92.0	86.7	69.7	97.0	79.3
LVLA	60.0	98.7	93.8	88.1	73.2

When the order is fixed at 3, the arousal classification accuracy is 82%, valence classification accuracy is 84% and the four class classification accuracy is 70%. The confusion matrix is shown in Table 4.31and error analysis in Table 4.32.

Table 4.31: The confusion matrix on frontal and parietal electrodes using differential average ERPs with SVM polynomial order set at 3

Confusion Matrix on Frontal and Parietal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	20	2	0	3
	HVHA	4	17	2	2
	HVLA	2	4	15	4
	LVLA	5	0	2	18

Table 4.32: The error analysis for results in Table 4.31

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	80.0	85.3	64.5	92.8	71.4
HVHA	68.0	92.0	73.9	89.6	70.8
HVLA	60.0	94.7	78.9	87.7	68.2
LVLA	72.0	88.0	66.7	90.4	69.2

4.6 Emotion Classification on Frontal Electrodes using Three Classifiers

In order to make a comparison between the methodology used by Frantzidis et al.(2010) and a two classifier technique used by us, two independent classifiers to classify low arousal and high arousal data into low valence and high valence classes have been used. The results obtained are shown in Table 4.33 and Table 4.34.

Table 4.33: The confusion matrix on frontal electrodes using average ERPs with one arousal and two valence classifiers

Confusion Matrix on Frontal and Parietal Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	22	2	0	1
	HVHA	1	23	1	0
	HVLA	1	3	21	0
	LVLA	6	0	2	17

As described earlier, the arousal classification accuracy is 88% at SVM polynomial order 6. After classifying arousal, two valence classifiers, one classifying low arousal emotional data into low valence low arousal(LVLA) and high valence low arousal(HVLA) classes and the second classifying high arousal emotional data into low valence high arousal(LVHA) and high valence high arousal(HVHA) classes have been used. In both the cases classification accuracy of 94% has been obtained at SVM polynomial order 4 and SVM polynomial order 5 respectively.

Table 4.34: The error analysis for results in Table 4.33

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	88.0	89.3	73.3	95.7	80.0
HVHA	92.0	93.3	82.1	97.2	86.8
HVLA	84.0	96.0	87.5	94.7	85.7
LVLA	68.0	98.7	94.4	90.2	79.1

The four class classification accuracy does not exceed the accuracy obtained using two classifiers i.e. 83%. As described in Section 3.7.3 in Chapter 3, the classification accuracy depends upon the index of trials wrongly classified along arousal and valence domain. If different test samples have been wrongly classified along arousal and valence, the four class classification may decrease even though the arousal and valence classification may be higher. When arousal and valence classification is done considering orthogonal relationship between arousal and valence domains, then separate classifiers should be used to classify arousal and valence. Therefore, either classification should be done using two separate arousal and valence classifiers or all the four classes should be classified simultaneously. It is important to mention here that when classifying low arousal and high arousal data along the valence domain, the same attribute set as was used when classifying emotions using two classifiers suited the best though at different orders. In other words, the attribute set that gives best accuracy for classification of low arousal data into valence obviously gives the best classification accuracy for classification of high arousal data along the valence axis. The CCI for this case lie in the range of 82 - 88 with accuracy range of 82 - 88% and mid range accuracy of 85% which is better than 75% obtained in case of Frantzidis et al. (2010).

In this Chapter 4 we have developed and analyzed four emotion classifiers on each electrode combination. The review of results is presented in Figures 4.2 - 4.5. The Figure 4.2 shows the results obtained with absolute average ERP attributes on different combinations of electrodes and best order of SVM polynomial classifier used for classifying emotions along arousal and valence. The results show significantly good accuracy results on different combinations of electrodes with average ERP attributes. The four class classification accuracy of 83% on frontal electrodes surpasses four class emotion classification accuracy of 81.3% reported by Frantzidis et al. (2010). When using frontal and parietal electrodes a four class classification accuracy of 75% has been obtained as shown in Figure 4.2.

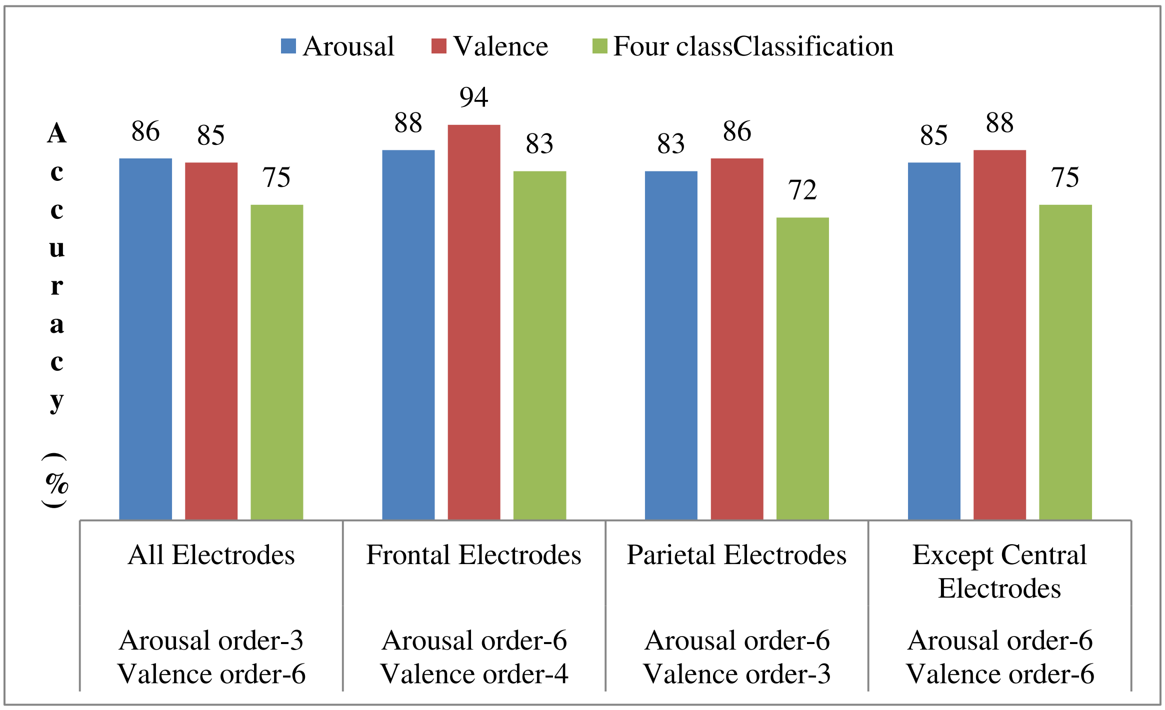


Figure 4.2: Accuracy obtained with absolute average ERP attributes on different combinations of electrodes

When the best order of SVM polynomial classifier is fixed at 3, the classification accuracies drop as compared to the accuracies obtained for the classifiers using best polynomial order determined between 3 - 6 as shown in Figure 4.3. However, four class classification accuracy remains above 67% for every case. As described earlier, the analysis has been performed on difference of average ERP attributes as well. The Figure 4.4 shows good classification accuracies with difference of average ERP attributes.

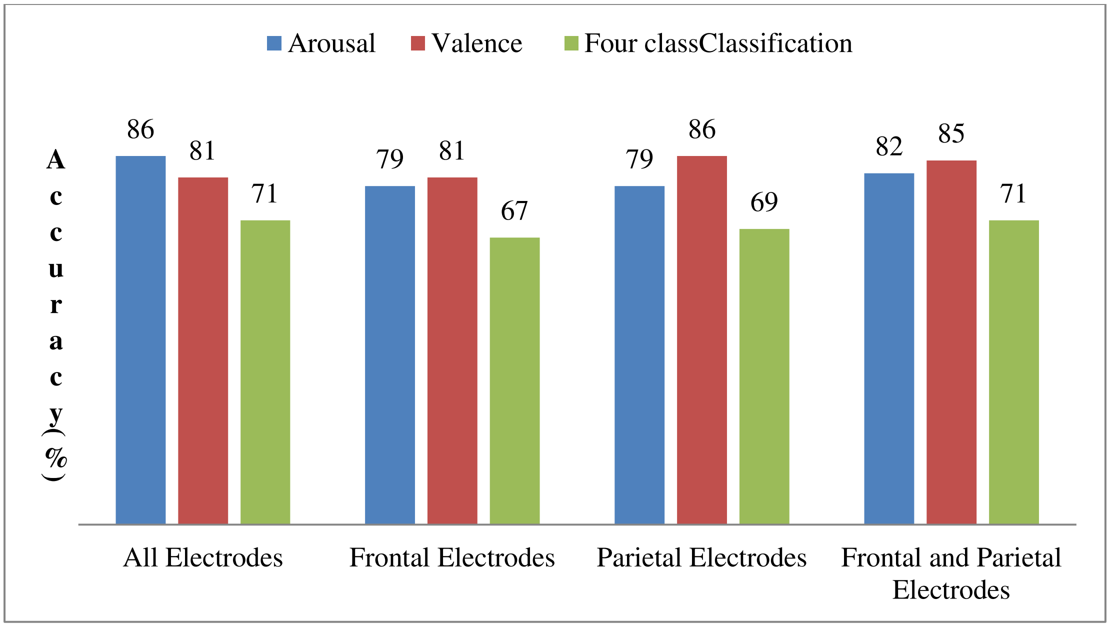


Figure 4.3: Accuracy obtained with absolute average ERP attributes on different combinations of electrodes with SVM polynomial order set at 3

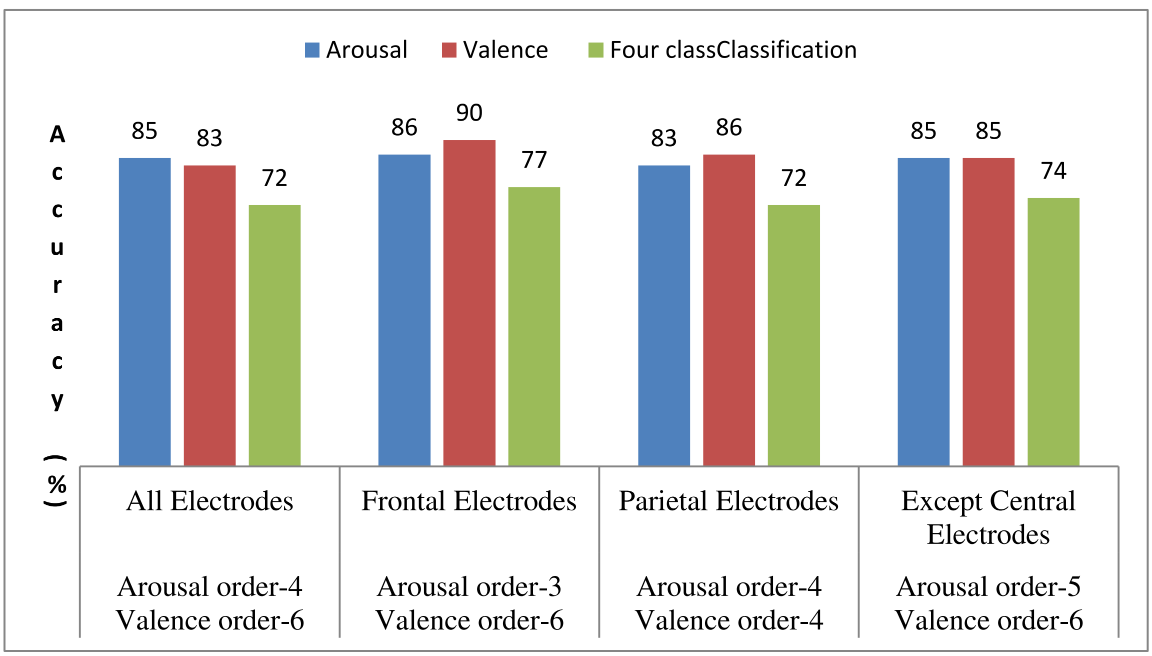


Figure 4.4: Accuracy obtained with difference of average ERP attributes on different combinations of electrodes

It can be seen from Figure 4.4 that the best emotion classification results have been obtained on frontal electrodes inline with emotion classification results obtained using average ERP attributes. Along the valence domain, a classification accuracy of 90% has been obtained on frontal electrodes. The four class emotion classification result remains above 70% on different combination of electrodes. It can be seen from Figures 4.2 - 4.4 that after frontal electrodes, highest classification accuracy is obtained on combination of frontal and parietal electrodes. The frontal electrodes and frontal-parietal electrodes giving best emotion classification results are inline with the studies of Hagemann et al. (1999), Davidson (2004), Petrantonakis and Hadjileontiadis (2010a), Hidalgo-Muñoz et al. (2013) and Menezes et al. (2017) . It is as well pertinent to mention that Jenke et al. (2014) found the variation in selected electrodes with the type of feature. In their study, mostly central or parietal electrodes were chosen for different features and with different feature selection methods. It is noteworthy to mention that the results using average ERP attributes are better than single trial EEG attributes when developing subject independent emotion classifiers.

The classification accuracies obtained using difference of average ERP attributes with SVM polynomial order fixed at 3 are shown in Figure 4.5.

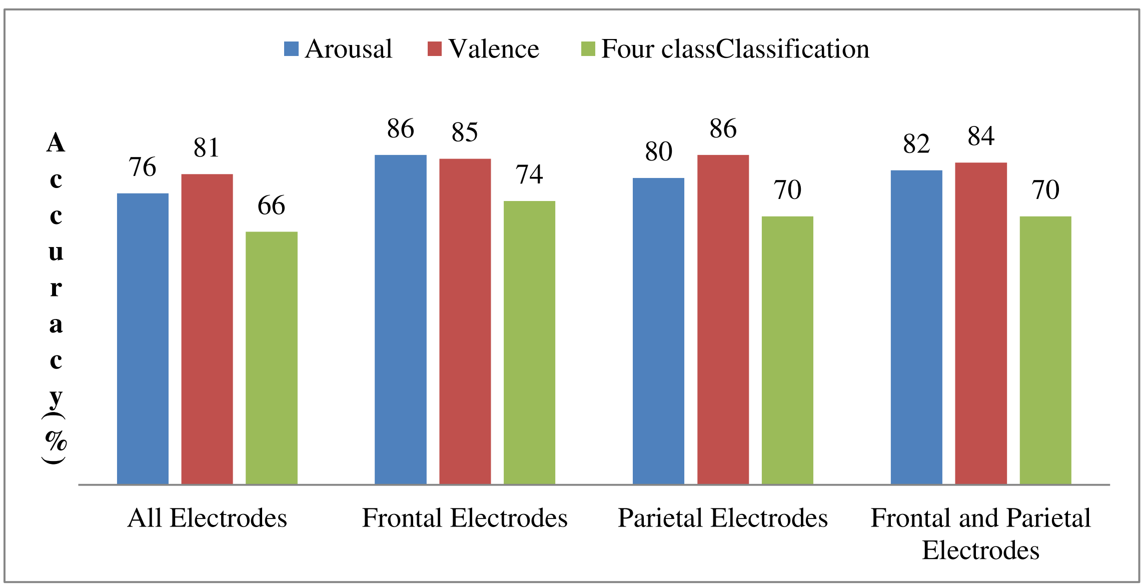
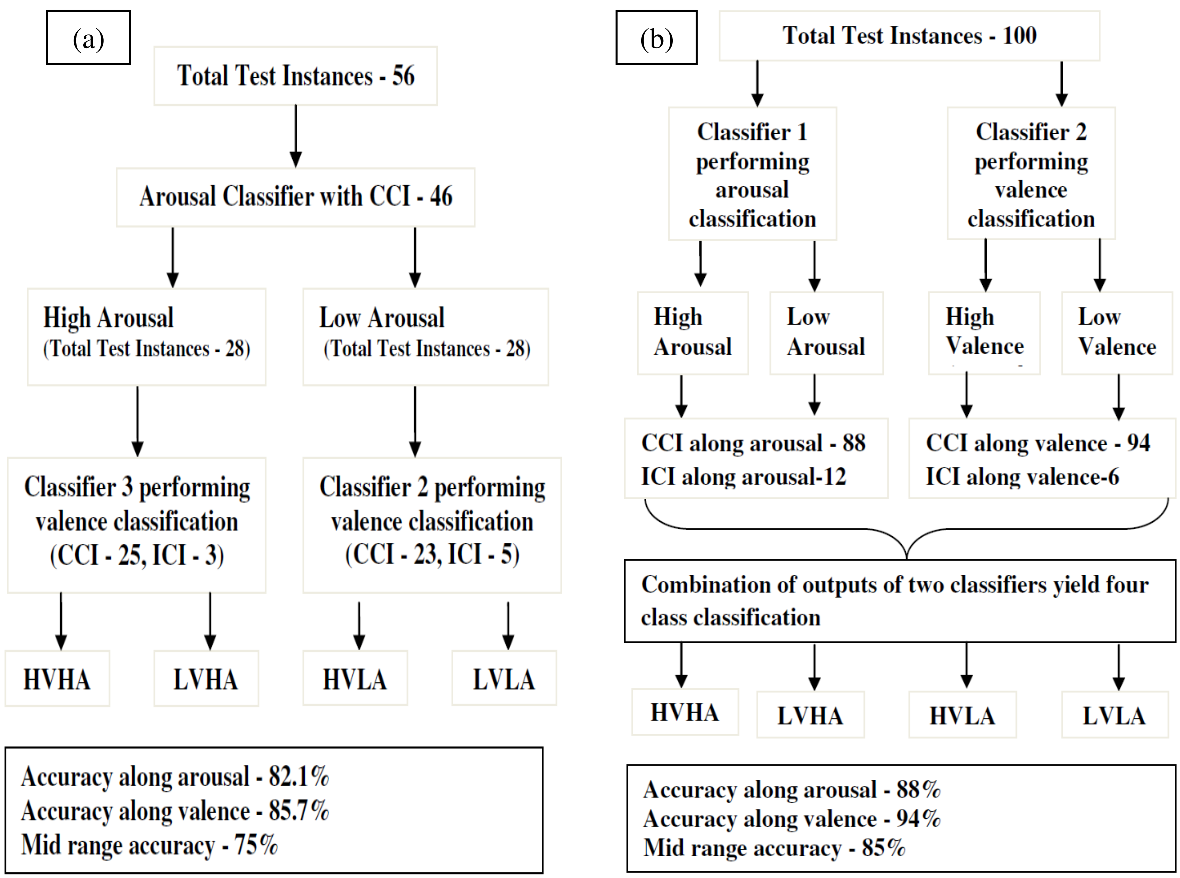


Figure 4.5: Accuracy obtained with difference of average ERP attributes on different combinations of electrodes with SVM polynomial order set at 3

4.7 Results and Discussion

In Chapter 4, the emotion classifiers on different combination of electrodes have been developed. The testing has been performed on 100 test instances such that 25 instances belong to each class of emotion, namely, LVHA, HVHA, HVLA and LVLA. The best four class classification accuracy of 83% has been obtained for a classifier developed using average ERP attributes acquired from frontal electrodes. Frantzidis et al. (2010) proclaimed a four class emotion accuracy of 81.3% by using different SVM classifiers (linear, RBF, polynomial) at different levels of classification. The results obtained by Frantzidis et al. (2010) are shown in Figure 4.6(a) and the results obtained from the proposed emotion classifier are shown in figure 4.6(b).



*CCI- Correctly Classified Instances, ICI-Incorrectly Classified Instances

Figure 4.6: (a) Results obtained by Frantzidis et al. (2010) (b) Results obtained by using proposed method on frontal electrodes using average ERPs on subject independent trials

Table 4.35: Comparison of results obtained by Frantzidis et al. (2010) and results obtained by using proposed method on frontal electrodes using average ERPs on subject independent trials

Comparative Analysis	Electrodes Used	Features Used	Possibility of Testing on Single EEG Electrode	Type of Classifier Used	Number of Classifiers used	Polynomial Order Used	Accuracy/ Total Test Instances
Classifier Proposed by Frantzidis et al. (2010)	Fz, Cz and Pz (Central Electrodes)	ERP and Event Related Oscillation. Number of Selected Features for Developing Emotion Classifier lie between 16-22	Not Possible	SVM linear, SVM polynomial SVM radial basis function	3 (1 for Arousal, 2 for Valence)	Arousal- 3 Valence- 3 and 2	81.3%/ 56
Classifier Proposed in this study	Fp1, Fp2, F3, F4, F8 and Fz (Frontal Electrodes)	Event Related Potential (Number of Selected Features for Developing Emotion Classifier always less than or equal to 12	Possible	SVM polynomial	2 (1 for Arousal, 1 for Valence)	Arousal- 6 Valence- 4	83%/ 100

The comparison of results in Figure 4.6 shows that the proposed classifier has been tested on 100 instances as comparison to 56 instances tested by Frantzidis et al. (2010). The proposed classifier in this study uses orthogonal nature of arousal and valence and thus employs two classifiers to achieve four class emotion classification instead of three classifiers. In classifier proposed by Frantzidis et al. (2010), the correctly classified instances (CCI) along the arousal were 46 and along the valence were 48. This means, the ICI would lie in the range of 10 - 18 resulting in accuracy in the range of 67.9 - 82.1%. The mid range accuracy is hence 75%. However for four class emotion classifier proposed in this study, accuracy along arousal is 88% and accuracy along valence is 94% as compared to 82.1% along arousal and 85.7% along valence proposed by Frantzidis et al. (2010). Accuracy of 88% and 94% along arousal and valence domains respectively point to ICI in the range of 12 - 18 and four class emotion classification accuracy in the range of 82 - 88%. The mid range accuracy is thus 85%. The Figure 4.6 depicts that the proposed emotion classifier is better in terms of accuracy (four class, arousal and valence), methodology used and number of classifiers used to classify emotions. The proposed classifier is better in performance on account of electrode selection, order of Support Vector Machine (SVM) polynomial classifier and feature reduction as shown in Table 4.35. It is further imperative to mention here that Frantzidis et al. (2010) used three types of SVM classifiers to achieve an overall accuracy of 81.25%.

4.8 Summary

In this Chapter emotion classification analysis (subject independent) has been performed on different sets of electrodes viz; all 10 electrodes, frontal, parietal and frontal and parietal electrodes by using absolute average ERPs and differential average ERPs. Further, classification results have been reported by keeping the SVM polynomial order fixed at default value 3 as well as by determining the best order. Some of the important findings are outlined below.

1) The best arousal (88%), valence (94%) and obviously four class classification accuracy (83%) has been obtained on frontal electrodes with absolute average ERP attributes.
2) When SVM polynomial order is fixed at 3, the classification accuracies remain higher than or equal to 70% for most of the electrode combinations with difference of average ERP attributes.
3) The results are better than obtained using single trial absolute ERP and difference of ERP attributes.
4) The use of three classifiers as reported in other studies for emotion classification causes meager change in emotion classification results. This has been validated by performing emotion classification using three classifier technique on frontal electrodes.

CHAPTER-5

TRANSITION OF EMOTIONS FROM NEGATIVELY EXCITED TO POSITIVE UNEXCITED STATE

5.1 Introduction

Mind has no physical existence. It is many times defined as the working of brain. When a person is in LVHA state, he is said to be negatively excited. Anger, frustration, disgust and tense etc. are few emotions which lie in this category. This is supposedly the worst category of emotional state. On the contrary, the best state of emotion is that of HVLA state in which the subject is positively excited. This category has emotions like calm, relaxed, at ease and glad etc. The endeavour of all psychologists is to bring the subjects from LVHA state to HVLA state. The review shows number of studies undertaken to carry out the transition of emotions. However, the studies validating the effect of meditation on transition of emotions through collection of physiological signals before and after the intervention are limited. After several trials of different interventions, it has been found that guided meditation have remarkable effect in bringing the subjects from LVHA state to HVLA state. One such guided meditation has been designed to involve progressive relaxation among the subjects. This is about half an hour meditation which requires simple preparation like sitting in a silent room with minimal disturbance. The subjects who are identified to be in LVHA state for any reason have been voluntarily asked to undergo half an hour meditation. The main emphasis in this study is classification of emotional states using the proposed technique of ERP/EEG. We identified 20 subjects for data collection and analysis.

5.2 Experimental Methodology

To identify the subjects for our experiment, we specially conducted one workshop for students of Thapar University, Patiala. Most of the students belonged to 3rd and 4th year of their under graduation program. Some of the students who participated in this workshop have been our subjects during our endeavour to collect data for emotion recognition. For others it was an informative talk in which we explained to them about emotions, 2-d arousal-valence plane, the non invasive experimental technique and the meditative intervention technique intended to be used in our experiment. Apart from experimental methodology, the information about the various states of emotions such as low valence high arousal (LVHA), high valence high arousal (HVHA), high valence low arousal (HVLA) and low valence low arousal (LVLA) were explained. The Figure 2.2 in Chapter 2 was very helpful in this regard. The Figure 2.2 is reproduced over here for quick reference.

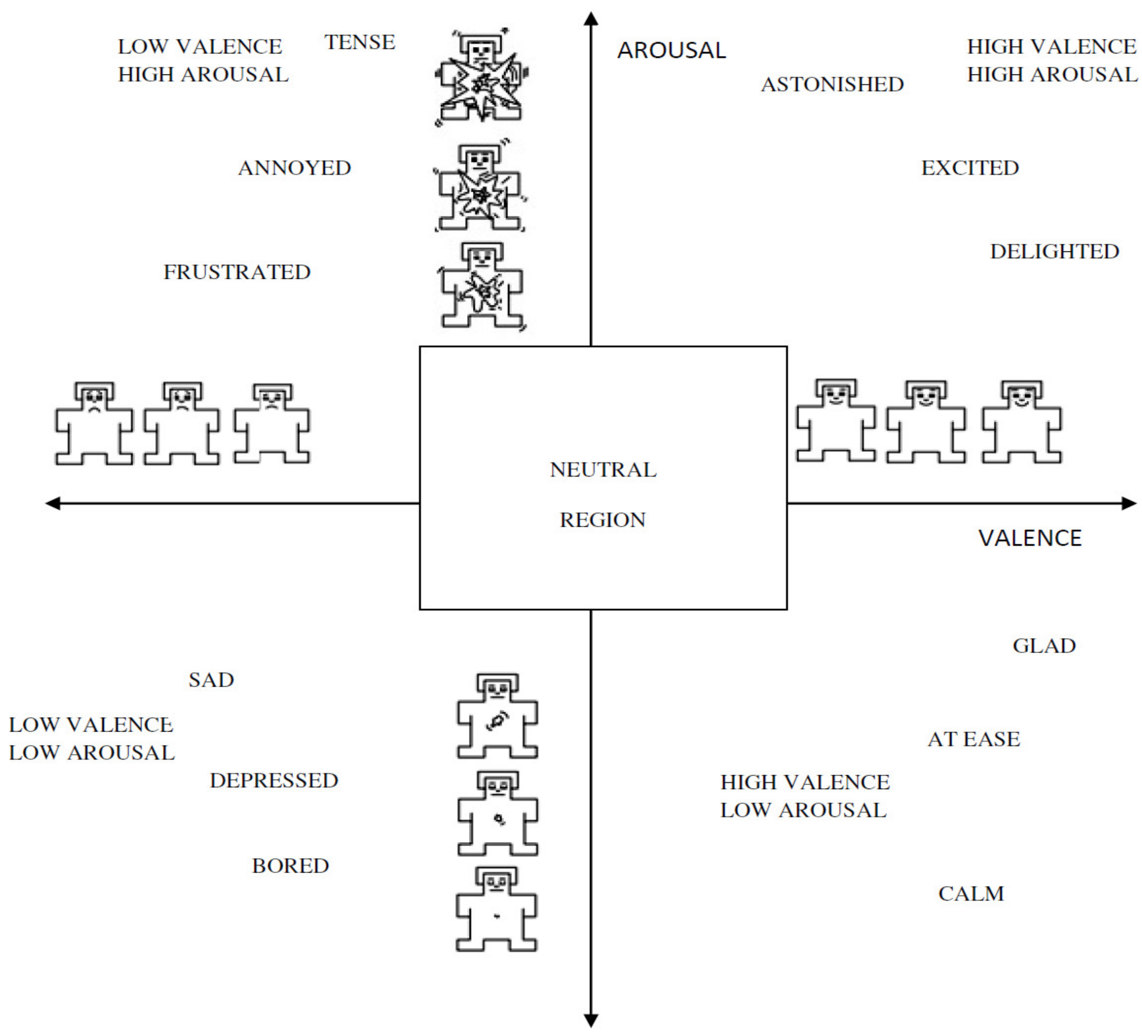


Figure 2.2: Demonstration of four classes of emotion on arousal-valence plane

To some curious subjects the meditative intervention technique in mp3 format was played for nearly 30 minutes. Further, we informed the participants that the identity of subjects shall be kept confidential, the experiment has been approved by the university ethics committee and the subjects specifically in LVHA are needed to carry out the intervention technique.

5.2.1 Data Acquisition Methodology and Feature Extraction

The EEG signals have been acquired on the subjects twice, one before the meditative intervention and secondly after the meditative intervention. The subjects visited experiment room on different days spanning three months. Since the emotions are said to be short and intense, we tried to get the pre and post meditative intervention EEG acquired in the shortest time possible from two frontal electrodes F3 and F4. It is worth mentioning that the protocol followed for EEG acquisition and processing operations on the EEG data acquired before and after the meditative intervention are same. The EEG data in any case i.e. premeditation or post meditation was acquired at a sampling frequency of 500 samples per second using Biopac MP150 system. The preprocessing operations involved notch filtering to remove 50Hz power noise and bandpass filtering using IIR filters to bring EEG signals in the range of 0.5 to 40 Hz as described in Chapter 2 and Chapter 3. The acquisition software Acq4.2 has been used to perform filtering operations. The ERP features were acquired in response to neutral images. A neutral image such as a plus symbol on a white screen was shown for 1 second followed by a cross symbol on a white screen for 1.5 seconds. The epoch time of 2.5 seconds was fixed in line with emotion recognition methodology discussed in Chapter 2 and Chapter 3. The images have been taken from online sources and are shown in Figure 5.1.

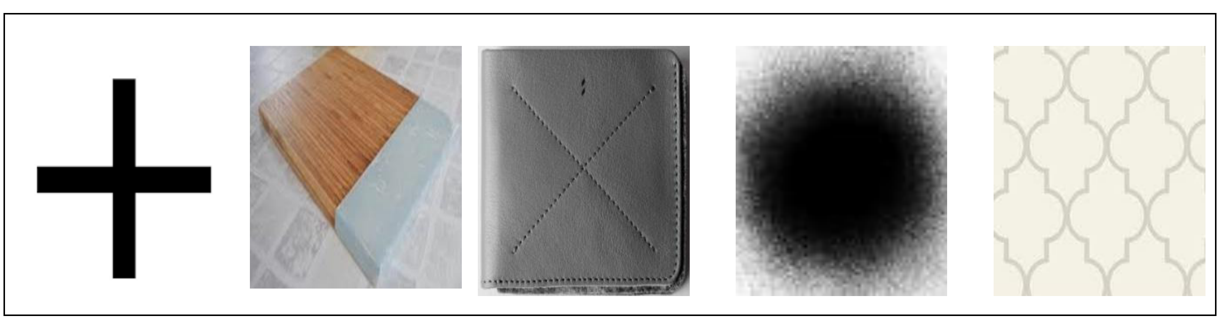


Figure 5.1: The neutral images used for EEG acquisition

The neutral images were chosen keeping in view the response of subjects to IAPS images. During data acquisition these neutral images were presented in a random order.

The EEG signals (before and after the meditative intervention) from each subject were acquired for twenty trials i.e. each neutral image was shown 4 times to the subject. The EEG signals spanning just lesser than 1 minute were acquired from each subject. From the averaged EEG signals, the ERP and latency features namely P100, N100, P200, N200, P300, N300, PT100, NT100, PT200, NT200, PT300 and NT300 were determined.

In pre meditative intervention mode, the EEG signals were acquired from those subjects who proclaimed (self assessed) themselves to be in the tense/angry/frustrated i.e. LVHA state of mind. During premeditation data acquisition, we played a screeching sound so that the subjects do not get settled and become neutral. After the premeditation signal acquisition, self assessment of subjects was taken. The subjects who assessed themselves to be in LVHA state of emotion went through the meditative intervention. An audio file in Mp3 format was played. This audio file guided the subjects to perform some simple meditative tasks and helped them achieve a calm state of mind. It was ensured that the subjects during intervention were not disturbed by any external activity. Some of the excerpts from the guided intervention are described below. The first four tasks are preparatory tasks to prepare the subjects for meditation. The main intervention starts with step 5. It is advised not to do meditation by reading these steps. It requires a thorough demonstration and close monitoring by properly trained meditation experts.

Preparatory Steps

1) Feel your breathing by putting a hand on your stomach.
2) Feel heart beat by putting your right hand on the heart.
3) Feel the pulse on your left wrist by using your right hand.
4) Produce a sound "OOOOOOOM" and at this point of time the distance between your teeth should be paper thin.

Meditation Steps

5) Close your eyes, stretch legs and relax your body
6) Monitor your body parts relaxing including fingers, neck i.e. the whole body is relaxing.

7) Think I am the happiest person in the world.

8) Keep smiling and feel your breath without making any noise.

9) Feel the depth of your breath as you breathe in.

10) Observe your breath coming deeper and slower, relax and smile.

11) Inhale relaxation and exhale out your worries, problems and negativity.

12) Feel the freshness and continue to breathe in at your pace.

13) Observe that the breathing speed is going down.

14) Witness the thoughts coming to your mind. Don't stop them but resist them.

15) Tell your thoughts "All lines to this route are busy".

16) Place right hand on your heart and feel your heart beat.

17) Put your heartbeat to productive and positive deeds.

18) Monitor the breathing. Inhale positivity and exhale positivity. Keep smiling.

19) Monitor your pulse on left hand wrist using your right hand.

20) Count your pulse keeping your eyes closed.

21) Count till 50. (Here there is pin drop silence for about a minute)

22) Put your hands on your ears and listen to the sound of silence and after a few minutes listen back to me. (Again there is pin drop silence for about two minutes)

23) The next task is you are supposed to inhale and produce the sound "OOOOOOOM" with your hands on the ears. Repeat it for 10 times.

24) Move your hands down, inhale, and produce the sound "OOOOOOOM" with little space in your teeth. Repeat it 10 times.

25) Relax and keep smiling. Keep your eyes closed. Your mind is most receptive now.

26) Again produce the sound "OOOOOOOM" with make and break of your teeth but with hands on your ear. Repeat it 10 times.

27) Put your hands down, relax, your brain is fresh now.

28) Again monitor your breath, I am calm, I am relaxed.

29) Keep your eyes closed. (After a countdown from 20 to 1) Open your eyes and observe silence for as long as you can.

30) Feel your emotions and maintain silence. The meditation is over.

Each subject assessed his emotion after intervention. The EEG signals post meditative intervention were acquired in a similar manner as discussed before by using neutral stimulus as shown in Figure 5.1. The ERP features were extracted for classification using SVM polynomial classifier as designed in Section 4.3 in Chapter 4. The classifier model is subject independent and is based on absolute average ERP attributes obtained at frontal electrodes.

5.3 Emotion Classification Results on Pre-Intervention and Post-Intervention Data

The ERP features acquired for both pre meditative intervention and post meditative intervention cases on two frontal EEG electrodes have been tested using SVM polynomial classifiers developed on average ERP attributes of frontal electrodes. The performance of arousal and valence classifiers using absolute average ERP attributes is explicitly described in section 4.3 of Chapter 4.

On analyzing the test data of subjects acquired before meditative intervention, the output of classifier matched with the self assessment for 20 subjects i.e. these 20 subjects were placed in LVHA state through both self assessment and EEG classifier. All the subjects were right handed male subjects. After going through meditative intervention, one subject reported himself to be in LVHA state of emotion, three subjects reported themselves to be in HVHA state of emotion and 16 subjects reported to be in HVLA in self assessment after meditation. The intervention efficacy is thus 80%. The placement of subjects' emotions before the meditative intervention and after the meditative intervention on arousal-valence scale according to self assessment is shown in Figure 5.2.

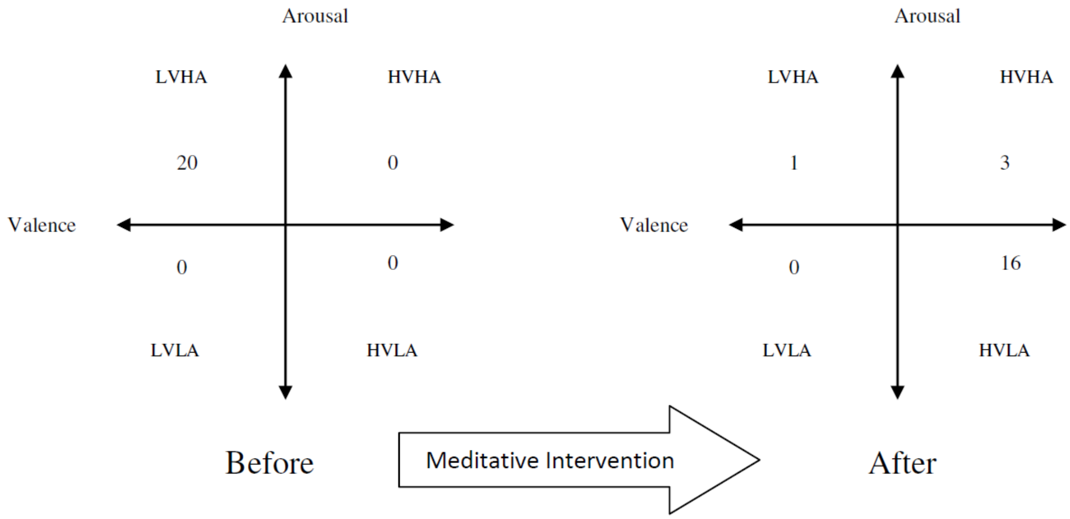


Figure 5.2: The effect of meditative intervention on emotions of subjects

5.4 Discussion of Results

It can be seen from Figure 5.2 that 16 subjects assessed themselves to be in HVLA state after intervention. Among these 16 subjects, 13 subjects were correctly classified in HVLA state, two subjects in LVLA and one in HVLA quadrant of arousal-valence plane. This gives a classification accuracy of 81.3%. Among the rest of the four subjects, one subject was correctly classified in LVHA state of emotion and two were predicted correctly in HVHA state of emotion. Thus the post meditative intervention on 20 subjects has been validated by the proposed classifier, arising in a confusion matrix shown in Table 5.1. From the four class classification confusion matrix, we obtained the error parameters given in the error analysis Table 5.2.

Table 5.1: The confusion matrix obtained on subjects post meditative intervention

Confusion Matrix on F3 and F4 Electrodes		Predicted Classes			
		LVHA	HVHA	HVLA	LVLA
Actual Classes	LVHA	1	0	0	0
	HVHA	1	2	0	0
	HVLA	0	1	13	2
	LVLA	0	0	0	0

Table 5.2: The error analysis for results in Table 5.1

Error Analysis	Sensitivity (%)	Specificity (%)	Precision (%)	Negative Predictive Value (%)	F1 Score (%)
LVHA	100.0	94.7	50.0	100.0	66.7
HVHA	66.7	94.1	66.7	94.1	66.7
HVLA	81.3	100.0	100.0	57.1	89.7
LVLA	NA	90.0	0.0	100.0	0.0

5.5 Summary

1) A meditative intervention technique to bring the transition from LVHA state of emotion to HVLA state of emotion has been discussed.
2) The intervention technique is about a 30 minute meditation process that helps relax human mind and body.
3) Among 20 subjects, 16 subjects reported themselves to be in HVLA state of emotion in self assessment taken post meditative intervention. This implies that the intervention efficacy is 80%.
4) The EEG signals (pre and post meditative intervention) have been acquired on F3 and F4 electrodes.
5) The use of SVM polynomial classifier developed on frontal electrodes correctly classifies 13 subjects in HVLA state of emotion validating the developed subject independent emotion classifier.

CHAPTER-6

CONCLUSION AND FUTURE PROSPECTS

6.1 Conclusion

Emotions play an important role in human life. Misinterpreted emotions can cause the loss of a relationship in many cases. Machine based recognition of emotions can be objective and accurate. This recognition is often done by acquiring and analyzing EEG signals. The development of emotion recognition systems is necessary to enhance human awareness of the social-psychological phenomenon which would further boost development in different spheres like designing human like robots, establishing the correctness of pharmaceutical and non-pharmaceutical interventions, screen out mission critical operations and detect/prevent cases of rage to name a few.

To classify evoked emotions in lab environment, mostly two computer systems are employed. One is used for projecting stimulus images. Another is used to put a marker on the EEG that is being continuously acquired at exactly the same moment of the projection of the image. This calls for synchronization of these two independent computer systems. This study describes design and development of a low cost synchronization technique for acquiring time locked EEG signals for emotion recognition. The technique developed to acquire EEG signals for emotion recognition is low cost and reliable, with acquisition lag staying within 1 millisecond for nearly 70% of the test keystrokes. For USB type keyboards, the synchronization error does not exceed 8 milliseconds. Our window of ERP is ±20 milliseconds and hence even this error is acceptable. EEG data of 24 subjects have been acquired in time locked manner using the proposed synchronization setup. A proper synchronization technique is required in every analysis of physiological signals acquired in response to external stimuli, whether it is a mind game, visual and/or audio stimuli. The novelty of this low-cost technique is that its use is just not limited to emotion recognition as it can also be used in experiments involving cognition enhancement based on meditation and games, where a pressing of a keyboard key will initiate a stimulus simultaneously putting a mark on the acquired physiological signal(s), thus generating completely and precisely time-locked physiological data.

An attempt has been made to develop a four class subject independent emotion classifier using ERP features of EEG. The four class subject independent emotion classifier based on multi trial ERP features has yielded satisfactory results (83%). The averaging of the EEG signals has been performed to remove the artifacts and noise. This certainly impacts the classification results when emotion classification is performed using average ERP attributes.

In this study, the best emotion classification accuracy along both the arousal and valence domains has been obtained at frontal electrodes viz; Fp1, Fp2, F3, F4, F8 and Fz. The good classification results impelled us to analyze the effect of meditative intervention techniques on 20 subjects.

Meditative intervention to bring the subjects which were in negatively excited state of emotion (LVHA) to positive unexcited state of emotion (HVLA) has been effectively developed. The intervention technique is validated by using the proposed classification technique.

6.2 Future Scope

The advantage of the emotion classification technique used in this research study is that it is simple with only filtering operations involved as preprocessing operations and uses very few attributes for developing emotion classifier such that any EEG electrode among the used could provide data for testing. However in this study, the proposed classification model is trained to classify emotions along arousal and valence domains correctly but classification along dominance axis was not considered. Considering the orthogonal nature of emotions, an independent classifier model can be developed to classify emotions along dominance axis as well in the future. In the proposed study, emotion classification operations have been performed by acquiring EEG signals only. In future, emotion classifiers using fusion of EEG, physiological signals and physical parameters, various physiological signals such as respiration rate, heart rate, GSR, body temperature and ECG and physical parameters such as color of the skin, eye gaze, eye blink rate and face patterns etc. need to be developed.

Nevertheless, this study is innovative and provides surplus options to be worked out in future such as using physiological signals in addition to EEG signals and using fusion at both feature and classifier level.

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