DISCRIMINATION BETWEEN GENUINE AND ACTED EXPRESSIONS USING EEG SIGNALS AND MACHINE LEARNING

by

Meera Alex

A Thesis presented to the Faculty of the
American University of Sharjah
College of Engineering
In Partial Fulfillment
of the Requirements
for the Degree of

Master of Science in
Biomedical Engineering

Sharjah, United Arab Emirates

April 2019

Approval Signatures

We, the undersigned, approve the Master's Thesis of Meera Alex

Thesis Title: Discrimination between genuine and acted expressions using EEG signals and machine learning.

Signature	**Date of Signature (dd/mm/yyyy)**
___________________________ Dr. Hasan Al Nashsash Professor, Department of Electrical Engineering Thesis Advisor	_______________
___________________________ Dr. Usman Tariq Assistant Professor, Department of Electrical Engineering Thesis Co-Advisor	_______________
___________________________ Dr. Hasan Mir Professor, Department of Electrical Engineering Thesis Co-Advisor	_______________
__________________________ Dr. Amer Zakaria Assistant Professor, Department of Electrical Engineering Thesis Committee Member	_______________
___________________________ Dr. Salam Dhou Assistant Professor, Department of Computer Science and Engineering Thesis Committee Member	_______________
______________________ Dr. Hasan Al Nashash Director, Biomedical Engineering Graduate Program	_______________
__________________________ Dr. Lotfi Romdhane Associate Dean for Graduate Affairs and Research College of Engineering	_______________
___________________________ Dr. Naif Darwish Acting Dean, College of Engineering	_______________
___________________________ Dr. Mohamed El-Tarhuni Vice Provost for Graduate Studies	_______________

Acknowledgement

I would like to thank my advisors Dr. Hasan Al Nashash, Dr. Usman Tariq, Dr. Hasan S Mir and Dr. Fares Al Shargie for providing knowledge, guidance, support, and motivation throughout my research stages. I am grateful for their assistance, and valuable discussions and suggestions.

I would like to thank the Biosciences and Bioengineering (BBRI) Research Institute for providing the lab equipment required to conduct this research. I appreciate all my advisors for dedicating their time towards this research. I would also like to thank the effort taken by my colleagues in the Emotion Monitoring Research team for helping me in conduct and organizing the research experiment. I acknowledge AUS for granting me graduate teaching assistantship during the course of this masters program.

Dedication

I would like to dedicate my work to my family.

Abstract

The main purpose of this thesis work was to quantify happiness in an objective manner. This is in line with the objectives of the National Program for Happiness and Positivity in the UAE. The major contribution to this thesis work included designing and conducting experiments to study the emotion-related cognitive process using EEG signals. The focus is to develop a novel method for classifying EEG signals related to genuine and acted expressions. A framework for quantifying three different affective states: actual/true positive, acted/fake and neutral positive emotions were developed. The major stages involved the development of an emotion related EEG database comprising of 28 subjects, feature extraction, and finally the application of machine learning algorithms. Two main approaches were used for feature extraction: the first method included discrete wavelet transform while, the second method involved a combination of discrete wavelet transform (DWT) and empirical mode decomposition (EMD). Average power features extracted from both the techniques were used for classification of the three affective states. Highest accuracy of 69.2 % using the DWT method and 94.2 % using DWT-EMD method was achieved.

Keywords: ***Empirical mode decomposition; Discrete wavelet transform; Emotions; Electroencephalogram***

Table of Contents

Abstract……………...6

List of Figures...9

List of Abbreviations 11

Chapter 1. Introduction 12

1.1 Overview……………………………………………………………….......13

1.2. Thesis Objectives………………………………………………….........13

1.3. Research Contribution...14

Chapter 2. Background and Literature Review..15

2.1. Background 15

2.1.1. EEG signal and brain regions.……………………………………….........16

2.1.2. Emotions associated with brain..………………………………………...18

2.2. Emotion classification based on EEG 18

Chapter 3. Methodology 22

3.1. Problem formulation 22

3.2. Proposed Method 22

3.2.1. Preprocessing……………………………………………………………….23

3.2.2. DWT……………………………………………………………..............23

3.2.3 EMD………………………………………………………………..........26

3.2.4 DWT-EMD……………………………………………………….... 28

3.2.5. Feature extraction……………………………………………….............29

3.3. Classification…………………………………………………………......30

Chapter 4. Experimental Setup 32

4.1. Participants...32

4.2. Stimuli Description 33

4.3. Data Collection 33

4.4. Experiment Paradigm...35

Chapter 5. Results and Analysis 37

5.1. Power Distribution Topographies and Statistical Power Distribution Topographies...37

5.2. Classifier Performance Evaluation..40

5.2.1. Classification performance using the DWT method……………………...40

5.2.2. Classification performance using DWT-EMD method…………… 42

Chapter 6. Conclusion and Future Work 46

References…………...48
Vita……………………..51

List of Figures

Figure 2.1: Valence-arousal model ………...16
Figure 2.2: Cortex subdivision………………………………………………............17
Figure 2.3: The five brain waves ………………………………………………....18
Figure 2.4: Emotion recognition process using EEG ………………………… …...19
Figure 3.1: Methodology……………………………………………………………21
Figure 3.2: Db4 wavelet component……………………………………………...23
Figure 3.3: Wavelet packet decomposition…………………………………………24
Figure 3.4: Empirical mode decomposition……………………………………....27
Figure 3.5: DWT-EMD..……..…………………………………………….......28
Figure 3.6: Classification model…..…………...…………………………………29
Figure 4.1: Experimental setup…………………………………………………...31
Figure 4.2: 10-20 electrode placement……………………………………….......33
Figure 4.3: Experimental paradigm…………………………………………….....34
Figure 4.4: Target image………………………………………………………….....35
Figure 5.1: Power distribution topography using DWT method………………….…37
Figure 5.2: Statistical T-map topography of EEG rhythms...………………………..37
Figure 5.3: Power distribution topography using DWT-EMD method..…………….38
Figure 5.4: Statistical T-map topography of EEG rhythms..………………………...38
Figure 5.5: Case 1: Average classification accuracy across all subjects using ANN, KNN, and SVM classifiers.…………………………………….............39
Figure 5.6: Case 2: Average classification accuracy across all subjects using ANN, KNN and SVM classifiers ………………………………………….40
Figure 5.7: Case3: Average classification accuracy across all subjects using ANN, KNN, and SVM classifiers ……………………………………….....40
Figure 5.8: Average classification accuracy across all subjects by using classifier level fusion across the three bands …………………………………41
Figure 5.9: Case 1: Average classification accuracy across all subjects using KNN, SVM, and ANN classifiers ……………………………………….....42
Figure 5.10: Case 2: Average classification accuracy across all subjects using KNN, SVM and ANN classifiers ………………………………….............42
Figure 5.11: Case 3: Average classification accuracy across all subjects using KNN, SVM, and ANN classifiers fusion ………………………….............43
Figure 5.12: Average classification accuracy across all subjects by using classifier level fusion across the three bands …………………………………....43

List of Tables

Table 3.1: Montage channel listing..33
Table 5.1: Comparison of classification accuracy using two feature extraction methods. 44

List of Abbreviations

EEG	Electroencephalogram
DWT	Discrete wavelet transform
EMD	Empirical mode decomposition
GSR	Galvanic skin response
HRV	Heart rate variability
PSI	Phase synchronization index
IMF	Intrinsic mode functions
KNN	K-th nearest neighbor
SVM	Support vector machine
ANN	Artificial neural network
EMG	Electromyogram
ECG	Electrocardiograph
GSR	Galvanic skin response
ST	Skin temperature
IAPS	International affective picture system
GAPED	Geneva affective picture database

Chapter 1. Introduction

Emotions play a vital role in human interaction. They influence decision making and human behavior. Emotions are due to intense mental activity. We express our emotions via verbal, facial and gestural means. The most general forms of emotions are happiness, fear, anger, disgust, sadness, and surprise [1]. The initial findings related to emotion research suggested that physiological changes cause emotions [1]. In previous studies, the analysis of signals and images related to physiological changes proved to be useful in emotion recognition and classification [1]. However, most of the past researches used methods like facial expression and speech tone analysis for understanding the underlying emotions. The emotion recognition studies using biological signals have gained popularity in recent years due to its continuous and spontaneous nature. This aids in capturing the unbiased state of mind. The techniques like facial expression analysis are liable to bias. This is mainly due to the fact that we human beings can consciously hide our emotions. Past researches have used physiological responses for emotion recognition in the past researches are Electrocardiogram (ECG), galvanic skin response (GSR), skin temperature (ST), and, electroencephalogram (EEG) are the common physiological responses used for [1], [3]. Among the various methods applied, physiological signals obtained from the brain are considered to be more reliable. EEG signals give high accuracy in time resolution and serve as an objective means of evaluation when compared to other methods. The brain is the main center for generating all emotions. Measuring EEG signals provide a direct measure of emotional process in the brain. Neural mechanisms exhibited by different emotions may be different. Existing emotion recognition techniques using EEG have utilized features extracted from the recorded brain waves and match it with the available emotion indexes. However, despite its relatively high accuracy, the traditional emotion analytics using EEG has some limitations in the classification of emotions. It is difficult to achieve more than a certain level of accuracy due to low-quality EEG signals acquired. Furthermore, it is not easy to define emotion indexes. The focus of this research work is to identify and define major electrode sites corresponding to happiness emotion. General focus will be on discriminating between genuine and acted smiles. In this chapter, we provide a short introduction to emotion recognition studies and the main objective of this study. Then, we present the problem investigated in this study as well as the main thesis contribution. Then we conclude the final section with the general organization of the thesis.

1.1 Overview

Emotion recognition studies using EEG follow a general scheme in most of the research. First step is the presentation of emotion-generating stimuli during EEG data recording and second step is the application of machine learning techniques to classify different emotions [1]. The way emotions are evoked plays a major role in recognizing emotions [3]. Most common ways of generating emotional states are by presenting pictures, videos or music. There are databases like International Affective Picture System (IAPS) that are used for visual stimuli presentations. Emotional stimuli presentation and data recording are followed by feature extraction and classification of EEG data. The different types of feature extraction techniques include frequency domain, time domain, time-frequency domain and functional connectivity features [1]. The time domain features employed in emotion recognition studies include classical statistical parameters, autocorrelation coefficients, fractal dimensions, and functional connectivity features. In frequency domain features like frequency band powers, power ratios, hemispheric differences, power ratios, spectral moments, signal entropy and higher order spectra are used. As discussed before, functional connectivity features are measures of coherence or phase synchronization index between time signals. The classifiers can be trained using extracted features. Past studies have used techniques like Support vector machine method (SVM), k-Nearest Neighbour (KNN), Linear Discriminant Analysis (LDA) and Artificial Neural Networks (ANN). However, the most preferred classifier technique is SVM method due to its low complexity in handling EEG signals.

1.2. Thesis Objectives

The main objective of this project was to observe the objectives of the National Program for Happiness and Positivity in the UAE. This project aims to quantify happiness in an objective manner. In this study, the emotion related to happiness is quantified by observing the cognitive response to an emotional stimulus. The focus is to develop a novel method for classifying EEG signals related to genuine and acted expressions. The main area of interest in this study is to study the brain's behaviour towards expressing a genuine and acted smile expression.

1.3. Research Contribution

The contributions of this research work can be summarized as follows:

- Distinguish between three positive emotions expressions: genuine smile, acted smile and neutral positive smile using machine learning method with EEG data. This scheme employs two approaches for studying the emotional processing by exploiting features at neuronal oscillations.
- Development of an EEG dataset that can be geared towards discrimination between genuine and acted expressions.

1.4. Thesis Organization

The rest of the thesis is organized as follows: Chapter 2 provides background about related previous studies in the area of emotion recognition with EEG. The employed methods and algorithms are discussed in Chapter 3 along with the implementation of the proposed methodology. Chapter 4 presents the experimental setup used for this study. Chapter 5 details the results and classifier performance evaluation employed the different emotion recognition algorithms used in this study. Finally, Chapter 6 concludes the thesis and outlines future work.

Chapter 2. Background and Literature Review

This section presents the background related to the emotion recognition studies and discusses relevant literature of previous studies pertinent to emotion recognition with EEG.

2.1. Background

Emotions are complex processes that can influence the physical and psychological behaviour of human beings during social interactions and decision-making processes [3]. They help in achieving intelligent and effective social communications [3]. Emotion involves three distinct components: a subjective experience, a physiological response, and a behavioural or expressive response [2]. There is a wide lot of research going on in the field of emotion recognition and classification. Majority of the studies focus on a few main classes of emotions: joy , fear, surprise, anger, disgust, sadness, etc. Available emotional models form the basis for characterizing emotions. Accordingly, the two most popularly used models re discrete and two or three-dimensional models. They are based on a continuous scale. This study primarily focuses on the two-dimensional model. The two-dimensional model is described based on arousal and valence scales. Valence scale discriminates emotions on a negative-positive scale and arousal is based on a scale ranging from calm to excited [6]. Figure 2.1 shows the arousal valence model for various types of emotions [4]. In discrete dimensional models, there are a fixed number of basic emotions like happiness, sadness, anger, etc. Scientists have used many different ways to analyse human emotions. From a broader point of view, we can classify them as subjective and objective measures. Mainly self-assessment of felt emotions and questionnaires are the subjective assessment of human emotions. However, subjective ways tend to be biased [6]. This is due to the fact that humans hide their feeling in order to meet social expectations. Thus, one additional motive behind this study is to focus on differentiating between genuine and acted emotions. Previous researchers have explored objective methods such as facial expressions, speech analysis, and other physiological measures for emotion detection. The use of physiological responses is one of the most prominent methods for characterizing emotions. The spontaneous nature of the physiologically recorded signal is the main reason behind its popularity among researchers.

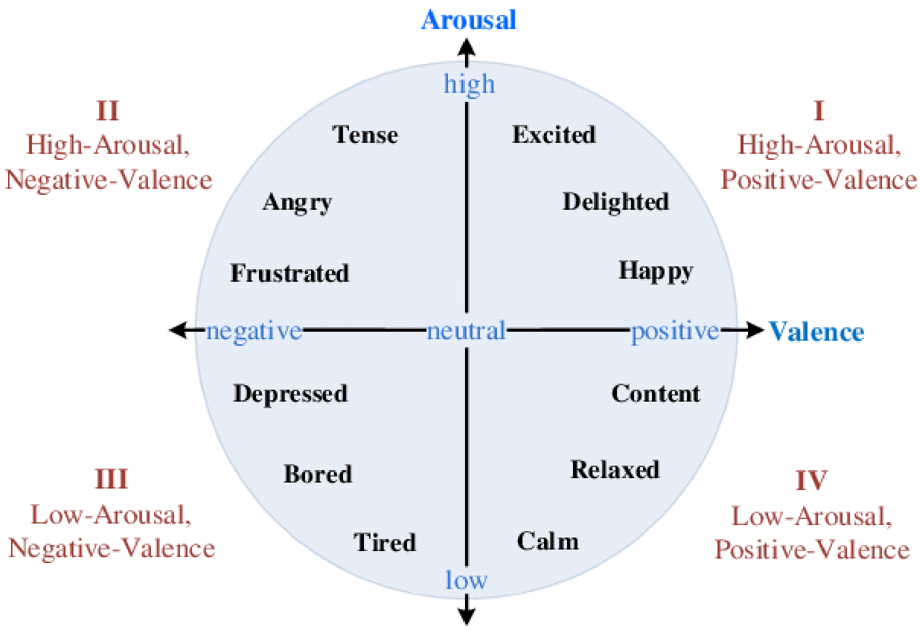

Figure 2.1: Valence-arousal model [4]

The most commonly used methods include Skin conductance (SC), respiration pulse, ECG, Electromyography (EMG), Galvanic Skin Response (GSR), Heart Rate Variability (HRV) and Electroencephalography (EEG)[33]. The method based on EEG signals is considered more reliable for emotion recognition. Wei-Long et.al [5] states that EEG signals are reliable due to their high accuracy and objectiveness when compared to other methods like facial expression. Non-invasiveness is another advantage of EEG measurement. This thesis report is based on emotion recognition system using EEG signals. The review of existing studies based on emotion classification using these signals is detailed in the following section.

2.1.1. EEG signal and brain regions. The human brain cortex is divided into the frontal, temporal, parietal, and occipital lobes (See Figure 2.2) [10]. The frontal lobe processes conscious thoughts. The temporal lobe processes olfactory, auditory senses and complex stimuli like faces and scenes. The parietal lobe integrates sensory information from various senses. The occipital lobe process vision [2]. The frontal lobe is the area where most of the conscious thoughts and decision-making takes place. This region is involved in cognitive processes like attention, short-term memory, planning, etc. due to the presence of dopamine neurons. Frontal lobe activities contribute to our personality and behavior since the activities in the frontal lobe help us in differentiating between bad and good actions, thinking over the consequences of the current actions, and predicting social behavior based on our past experiences and surroundings.

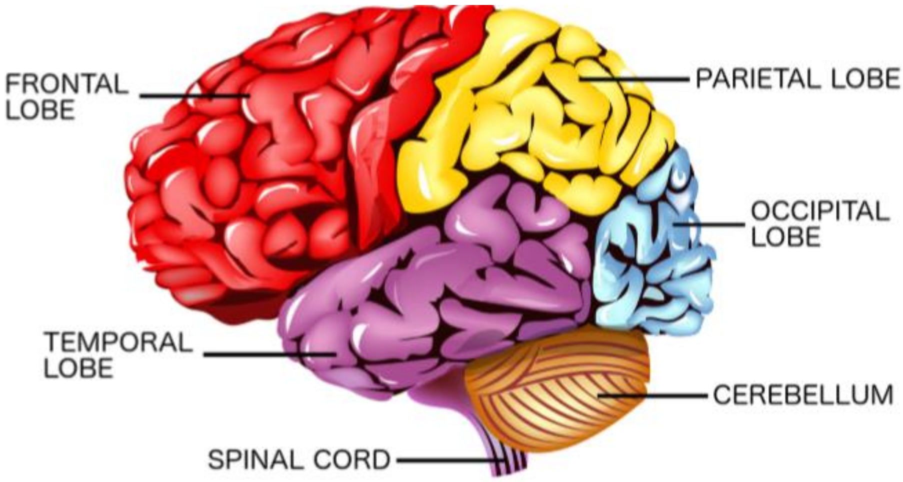

Figure 2.2: The cortex subdivided into the frontal, temporal, parietal, and occipital lobes. Adapted from [10].

EEG is a neuroimaging technique is used to detect electrical activity generated by brain structures. It measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. A typical EEG signal, recorded from the scalp, is about 10-100 μV [1]. The signals observed in the scalp are divided into specific frequency ranges which are more dominant in certain states of mind, namely the gamma (>30 Hz), beta (13-30 Hz), alpha (8-13 Hz), theta (4-7 Hz), and delta (1-4 Hz) bands [9] (see Figure 2.2).

Delta waves reflect the unconscious mind and occur during deep dreamless sleep. Theta brainwaves reflect subconscious mind state exist while sleeping and dreaming. Alpha waves reflect a relaxed, but awake mental state. They are visible in the occipital and parietal lobes. Beta waves reflect the active state of mind, which is more dominant in the frontal cortex. Finally, gamma waves reflect hyper brain activity [2].

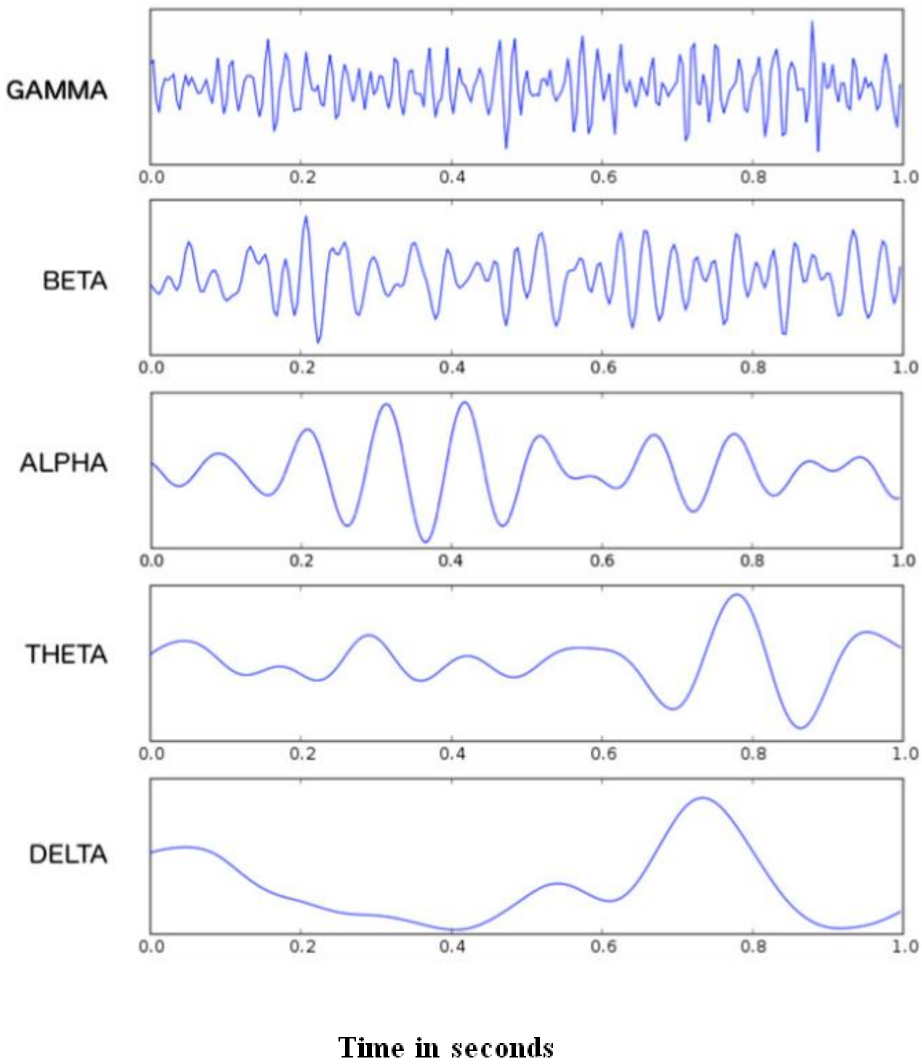

Figure 2.3: The five brain waves: gamma, beta, alpha, theta, and delta Adapted from [2].

2.1.2. Emotions associated with brain. Previous studies suggest that there is a correlation between EEG and emotions. Two main areas of the brain are known to be correlated with emotional brain activity: the amygdala and the prefrontal cortex [2]. The amygdala activation is mostly associated with negative emotions than positive ones [19].

2.2. Emotion Classification Based on EEG

A basic process involved in emotion recognition process is depicted in Figure 2.4. The studies of emotion recognition can be classified based on the assessment method and classification approaches used. Factors such as the number of subjects involved, experiment paradigm and emotion stimulation, etc. add to the complexity of developing an emotion detection system.

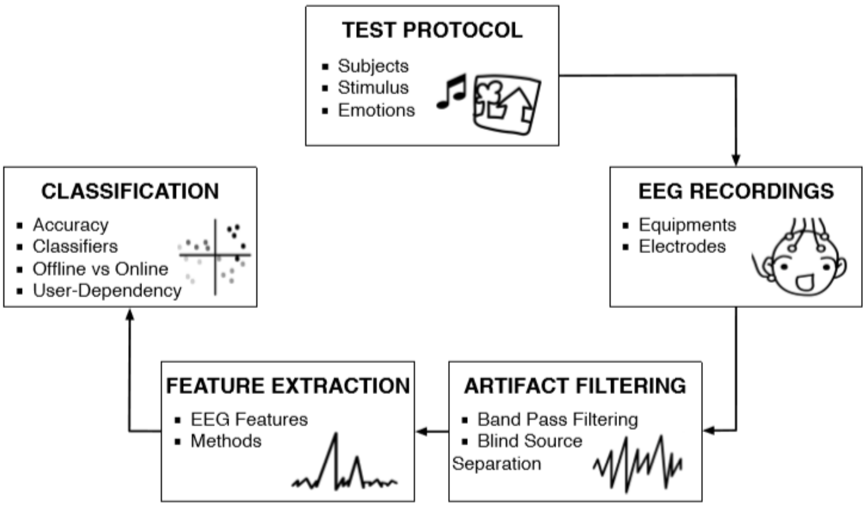

Figure 2.4: Emotions recognition process using EEG. Adapted from [17]

Y.-Y. Lee et al. in [11] used functional connectivity method as the assessment mode. This study was performed with 40 subjects and used 64 electrodes for EEG recording. Correlation, coherence and phase synchronization index (PSI) were the classification features extracted. This study was to distinguish between three emotions: positive, neutral, and negative. Using Quadratic Discriminant Analysis they were able to classify emotions with the highest accuracy of 75% by using PSI.

In the work done by Hanna Becker et al. the method of assessment was power spectral density [6]. EEG recording was taken from a 257 channel EEG system using video stimuli. The study included 40 subjects, attained maximum accuracy of 70% and 75% in the low and high gamma-bands, for sensor space features and source space features respectively. The research suggests that the reconstruction of brain sources prior to feature extraction improved the emotion recognition performance.

Z. Mohammadi et.al [26] used the, discrete wavelet transform method for emotion recognition. They used DEAP dataset for this study;- the classification accuracy was 86.75 % for arousal level and 84.05 % for valence level. According to this research high-frequency gamma band produced the highest accuracy compared to EEG signal at low-frequency band.

The technique of EMD was also explored in [27] on DEAP dataset. An average classification rate of 69.10% for valence and 71.99% for arousal was obtained for this study. The study showed that the first component of the IMF played a crucial role in emotion recognition.

Many emotion recognition studies used music as emotional stimuli. The study [28] used DWT assessment method to study the EEG signal related to listening music. However, they had only nine subjects for the experiment. An average classification rate of 86.52±0.76 % was achieved between emotion and state of rest. The results showed that activities in gamma and beta bands linked music preference and emotional arousal phenomenon.

O. Georgieva et al. [33] used event related potentials for assessing data collected from 26 subjects from 21 electrode recording system. This study classified positive and negative states with an accuracy of 88 % and 46 % respectively. It was found that the temporal features reduced inter-subject variability and improved the classification across multiple subjects.

S. Liu et al. [34] classified positive, neutral and negative emotions with mean accuracies of 72.50% at learning four days. Power spectral density was used for feature extraction. The study involved 17 subjects. The data was collected from 60 electrodes. The results imply that inter-day variability in the EEG recording impaired the performance of emotion and learning more day’s significantly improved the generalization of EEG-based emotion recognition over time.

Zheng et al. [35] conducted a study on multimodal emotion recognition using EEG and eye tracking data. EEG features used in this study were power spectral density and differential entropy. Similar feature was extracted from pupil data also. Positive, negative and neutral classified with 71.77% using EEG and 58.90% using eye tracking and 73.59 using feature fusion of EEG and Eye and 72.98% based on decision fusion. This study suggests that pupillary features improved the overall classification of emotions.

Y. Zhang et al. [36] used a combined feature extraction method approach for emotion recognition. However the data analysis was performed on already available emotion dataset DEAP. This dataset consists of 32 channel EEG data collected from 32 subjects. They achieved average classification accuracy of 93.20% for the multi-class task using EMD and sample entropy. This claims that EMD technique outperforms existing feature extraction methods on DEAP datasets.

Another emotion recognition study conducted by X. Li et al. [37] compared results from SEED and DEAP dataset for analysis by extracting power spectral entropy feature. There were 23 subjects involved in this study. This study was conducted to validate the possibility of exploring robust EEG features in cross-subject recognition. Positive, negative and neutral states were classified with an average accuracy of 59.06% on the DEAP dataset and 83.33% on the SEED dataset.

EEG based classification of emotions using empirical mode decomposition and autoregressive model was performed by Y. Zhang et al. [38] using DEAP dataset. The average recognition rate was 86.28% for four binary-class tasks on this dataset. The results from this method showed uniform and stable performance.

Chapter 3. Methodology

This chapter describes various steps involved in emotion recognition and classification. Figure 3.1 shows the block diagram of the description of this methodology. The major steps are data acquisition, signal processing, feature extraction, and classification.

3.1. Problem Formulation

Emotions are conscious experiences that have the power to influence our psychology and behavior. One of the most common ways of expressing emotion is by means of facial expressions. Smiling is one of the simplest positive emotional expressions. However, whether smiling truly indicates happiness or not depends on the mental state of a person. From a subjective point of view, asking questions helps in understanding what a person feels. Some people might fake emotions and facial expressions. Many studies have proven that subjective conclusions are unreliable. Thus, there is a need to devise a methodology to track what is truly going on in the mind. We need methods for analyzing brain activity to understand how the brain responds while expressing these emotions. The motive behind this is that brain signals reflect the true emotions. The methodology employed in this study in order to distinguish between genuine acted and neutral smile expressions is detailed in the following section.

3.2. Proposed Method

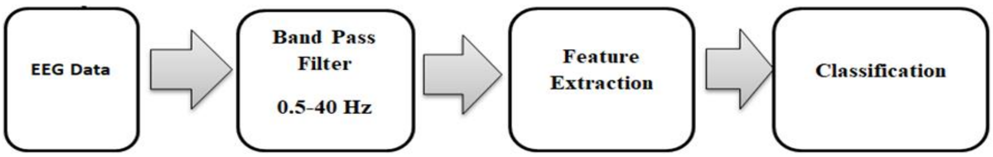

Figure 3.1: Methodology

The analysis of the EEG signal requires the extraction of specific details from the collected response for building accurate data classifiers. A variety of features can be extracted from the recorded EEG activity. According to the literature, there exist many classes of feature extraction techniques like time domain, frequency domain, time-frequency domain, functional connectivity, source localization, etc. [6]. In the article [19] it has been stated that neural oscillations and their synchronization give insight to underlying mechanisms related to inter-neuronal communication and information binding processed in distributed brain regions. Thus in the study feature extraction based on time-frequency analysis has been adapted. Two techniques have been used to study the emotion-related EEG signals.

3.2.1. Preprocessing. EEG signals were pre-processed offline by employing a band-pass filter of 0.5-40 Hz in the EEG lab. Sixty-four EEG channels according to the 10-20 system, were selected against the average reference. Blinking, detected by visual inspection. Other artifacts were manually removed by discarding those portions from the recording.

3.2.2. DWT. The EEG signals possess complex characteristics due to their non-stationary and nonlinear behaviour. Over the years, researchers have found many signal analysis methods to study EEG signals. Spectral analysis is one of the widely used analysis tools for EEG studies. Spectral methods can identify basic rhythms present in the EEG signal. However conventional methods like Fourier analysis assume signal to be stationary despite the fact that interesting process associated with EEG is often reflected in fast dynamic changes of the signal [7]. The main reasons for which Fourier analysis is unsuitable for real signals in nature have been pointed out in [8]. Fourier spectrum defines uniform harmonic components globally and require additional harmonic components to simulate non-stationary data that are non-uniform globally [8]. As a result of this wide energy distribution can be observed frequency domain. Considering, these facts the time-frequency method of analysis has been chosen for this study. Roughly, time-frequency methods are divided into two categories [7]:

1. Direct continuous energy density estimators in the time-frequency space

2. Techniques that decompose a signal into its frequency components.

Cohen's class of time-frequency distribution belongs to the first category. It requires no predefined decomposition and allows maximal flexibility in expressing the time-frequency contents of the signal. However, it suffers from a few consequences such as lack of parametric description and interference of signals [7]. The methods in the second class are STFT (Short Time Fourier transform), CWT (Continuous Wavelet Transform), DWT (Discrete Wavelet Transform), MP (Matched Pursuit) and, Hilbert-Huang transform. STFT and CWT are atomic representations of signal only provide certain parametric distributions. This representation is not much informative. DWT technique provides a sparse representation of the signal that results in an efficient parameterization of the time series. The sparse transformation also reduces reconstruction error. This study uses wavelet packet based decomposition of emotion-specific EEG signal. This is realized with MATLAB's 'wavedec' toolbox by defining wavelet decomposition level and type of wavelet packet. The discrete wavelet transform, T_x , for a signal $x(s)$ in the time domain can be defined as [7]:-

$$T_x\,(n,m;\psi) = \int_{-\infty}^{\infty} x(s)\psi_{n,m}^{*}(s)ds; \qquad (1)$$

Where $\psi_{n,m}^{*}$ is a scaled and translated version of ψ (fundamental mother wavelet).

$$\psi_{n,m}\,(s) = \frac{1}{\sqrt{a}}\psi\left(\frac{s-t}{a}\right) \qquad (2)$$

Where *s* is the time domain value, *t* is the time translation, *a* is the dilation and *n*, *m* are their respective scaling parameters.

In this study, DWT with the following parameters was used: Daubechies wavelet of Db4 (see Figure 3.2) and decomposition level of seven. Db4has been used in previous EEG based studies [13], [14]. The use of Db4 wavelet in emotion studies has been highlighted in [14] for having a near optimal time-frequency localization and similarity to EEG signal waveform. This gives good applicability to study of emotion using EEG signal.

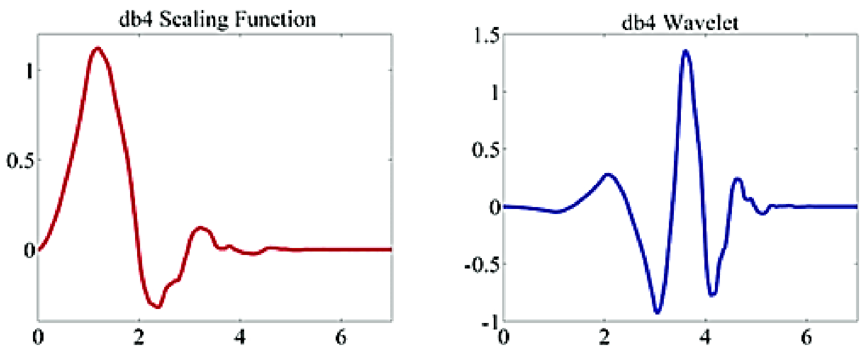

Figure 3.2: db4 wavelet component [34].

In the Figure 3.2 a typical Db4 scaling component is illustrated. This is similar to an EEG signal. Wavelet packet decomposition can be studied in terms of low and high pass filters to obtain required level of decomposition.

One of the governing conditions for specifying all wavelet transform in terms of a low pass filter G is the standard quadrature mirror filter condition [15]:

$$\mathrm{G(z)G(Z^{-1}) + G(-Z)G(-Z^{-1}) = 1} \tag{3}$$

where $\mathrm{G(z)}$ denotes the z-transform of the filter G.

The mirror of this is a high pass filter H, defined as:

$$\mathrm{H(z) = ZG(-Z^{-1})} \tag{4}$$

where H(z) denotes the z-transform of filter H. The sequence of filters with increasing length can be found from:

$$\mathrm{G_{i+1}(z) = G(Z^{2^i})G_i(z)} \tag{5}$$

$$\mathrm{H_{i+1}\,(z) = H\left(Z^{2^i}\right)G_i(z),\ \ i = 0, \dots \dots l - 1} \tag{6}$$

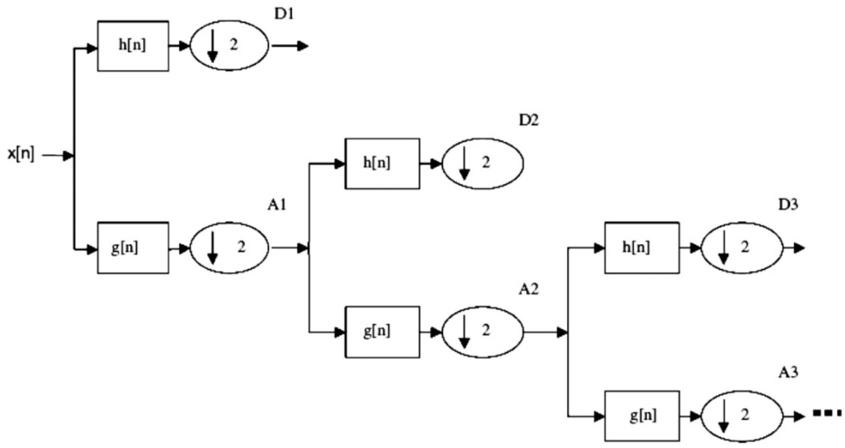

Figure 3.3: Wavelet packet decomposition [15].

The detail D1 and approximation A1 are the outputs of the first high low pass filter as seen in Figure.3.3. Wavelet packets are a modification of DWT decomposition method. It involves two steps:

1. Modification of filter/down-sampling cascade to make a decomposition tree.
2. Selecting the most suitable decomposition of a given signal known as the pruning of a decomposition tree [7].

At each level in the wavelet packet scheme, two digital filters are engaged and down-sampled by a factor of two. The output of high and low pass filters provide the detail and approximation coefficients respectively at each decomposition levels. Later feature extraction is performed on the coefficients. In this study decomposition level, 4,5,6 were selected for feature extraction in which level 4 corresponds to beta band frequency (13-30 Hz); level 5 corresponds to the alpha band (8-12 Hz) and level 6 corresponds to the band theta (4-7 Hz).

3.2.3 EMD. EMD is a time-frequency method based on Hilbert transform. The method was first proposed by Huang et al. [20]. It involves breaking down a signal without leaving the time domain. EMD method is similar to other traditional analysis methods like Fourier Transforms and wavelet decomposition. One of the major advantages of EMD is that it can deal with EEG signal's non-linear and non-stationary nature. Fourier transform assumes uniform harmonic components globally. Thus, it requires many additional harmonic components to simulate non-stationary data globally. This results in the spread of the signal energy over a wide frequency range [20]. The EMD methods generate a collection of intrinsic mode functions (IMF). It extracts direct energy associated with various intrinsic time scales. The local energy and the instantaneous frequency derived from the IMF through the Hilbert transform gives the full energy distribution of the data. This will be ideal for nonlinear and non-stationary data analysis [21].

The process of EMD begins by breaking down a signal into its component IMFs. An IMF is a function that has only one extreme between zero crossings, and the zero mean value. A sifting process is used to breakdown the signal into IMFs (See Figure 3.4). The sifting process is as follows:

- For a given signal $X(t)$, let m_1 be the mean of its upper and lower envelopes as determined from a cubic-spline interpolation of local maxima and minima.
- The first component $h_1$is computed :

$$h_1 = X(t) - m_1 \tag{7}$$

- In the second sifting process, h_1 is treated as the data m_{11} is the mean of h_1:

$$h_{11=}\ h_1 - m_{11} \tag{8}$$

- This sifting process is repeated k=1…k-1 times until h_{1k} is an IMF, that is :

$$h1_{k-1} - m_{1k} = h_{1k} \quad (9)$$

h_{1k} is designated as c1, which is the first IMF component from the data. This is the shortest period component of the signal. It is separated from the rest of the data:-

$$X(t) - c1 = r1 \quad (11)$$

$r1$ is the first residue component.The same procedure is repeated N times until $\mathrm{r_N}$ which is the residue component.

Thus the EMD of the signal X is:

$$X(t) = \sum_{i=1}^{N} c_i(t) + r_N\ (t) \quad (12)$$

The EMD results produce N IMFs and a residue component. Figure 3.4 demonstrates the decomposition of the EEG signal into four IMFs. EMD technique can be viewed as a time-scale analysis. Each IMF represents the intrinsic mode characteristic of non-stationary and nonlinear signal at various scales. Intrinsic mode functions are indicative of oscillations imbedded in the data. The IMF in each cycle is defined by the zero crossings and has only one mode of oscillation. It involves no complex riding waves. Thus an IMF is not a narrow band signal, but both amplitude and frequency modulated. Due to the adaptive nature of EMD, we cannot predict the number of IMFs generated. However, first four IMF possess all the necessary information required to completely define an EEG signal and its essential frequency components. As seen in the Figure 3.4 the frequency components are reduces each time decomposition is performed. This study takes the average of first three IMF components for feature extraction purpose. Many previous studies used EMD as a tool for de-noising EEG signals. Often EEG signals are polluted with power line interference and signals from other sources such as electromyogram. In the next section DWT-EMD method is discussed.

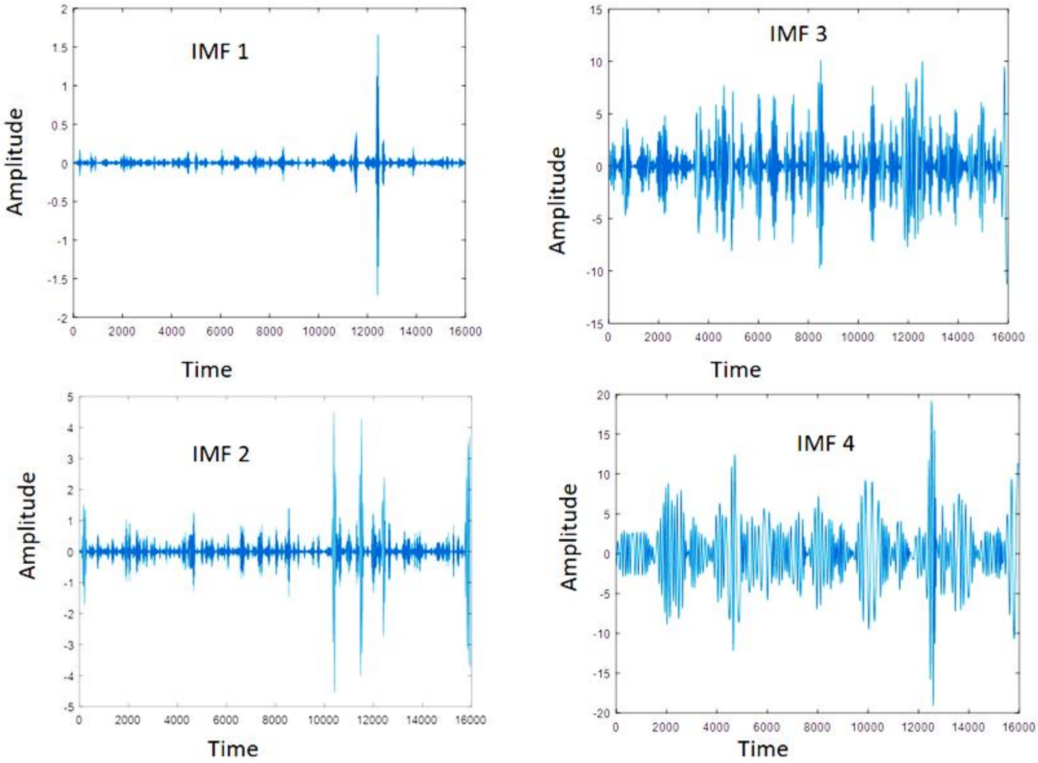

Figure 3.4: EMD decomposition of EEG signal into four IMF components

3.2.4 DWT-EMD. In this study, a combined DWT-EMD is applied for feature extraction. Figure 3.5 shows the DWT-EMD method. The emotion-specific EEG data is first subjected to wavelet transformation to get devoid of the mode mixture problem in the subsequent EMD procedure. This is in view of the fact that the straightforward application of EMD to the original data may lead to intermittencies [24]. Also, results from previous studies suggest that the combination of EMD and wavelet decomposition can retrieve effective characteristics present in nonlinear signals [25]. Although wavelet transform has better frequency resolution compared to tradition Fourier spectrum analysis there exists a trade-off in the resolution at high and low frequency [23]. The IMFs generated in EMD technique provide a full energy-frequency-time distribution of the data [22]. The using wavelet transform before EMD on the clean EEG signal is advantageous as it can detect and characterize singularities [14]. It has been reported in [23] that EMD techniques exhibit overall softening of and reduction of noise [13]. Thus, EMD can suppress noise accumulated from wavelet transformation [24]. The lack of adaptability from wavelet analysis is compensated by incorporating EMD analysis. EMD is fully data-driven adaptive techniques that preserve the locality of the original data [22].

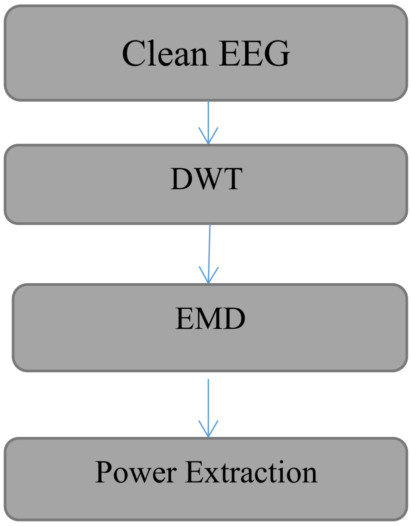

Figure 3.5: DWT-EMD

3.2.5. Feature extraction. The clean EEG signal is decomposed into the three frequency bands is the first step before applying feature extraction. The labeling of three conditions is done in accordance with response from the subject towards the image stimuli. For each condition (true smile, fake smile, and neutral smile), epochs were extracted. Each epoch had 550 data points. The data epochs were decomposed into their corresponding oscillations using the DWT method and DWT-EMD method. For each frequency band decomposed using DWT and DWT-EMD method, mean power feature was calculated using a moving time-window of 550 milliseconds for each EEG electrode. The following equations explain this method [17]:

$$P_j = \frac{1}{N} \sum_{n=1}^{N} \left| x_j\ (n) \right|^2 \qquad j = 1,2,3 \qquad (13)$$

where P_j is the EEG power, $x_j\ (n)$ represents the segmented EEG signal in the Alpha band at j = 1, Beta band at j = 2, Theta band at j=3 and N is the length of the signal. The power extracted from each band is fed into the classifier. These features were tested in the classifier with features extracted from both EMD and EMD-DWT.

3.3. Classification.

The two-way binary classification has been used in this study to distinguish between three cases of emotion namely case1: True versus fake smile; case2: True versus neutral smile and case3: Fake versus neutral smile. Three different types of the classifier were employed: k-nearest neighbour, artificial neural network and support vector machine. For two classes we can define the input matrix X as:

$$X_i = [X_{1,} X_2]^T \tag{14}$$

where X_i is a matrix with all the feature vectors belonging to class i, with M features, the size of X_i is $N \times M$. In here, N is the number of channels used. Categorical target labels were used to predict classes in the testing and training phase. The training and testing data set were created using 5 fold cross validation. Figure.3.6 shows the classification model used in the study.

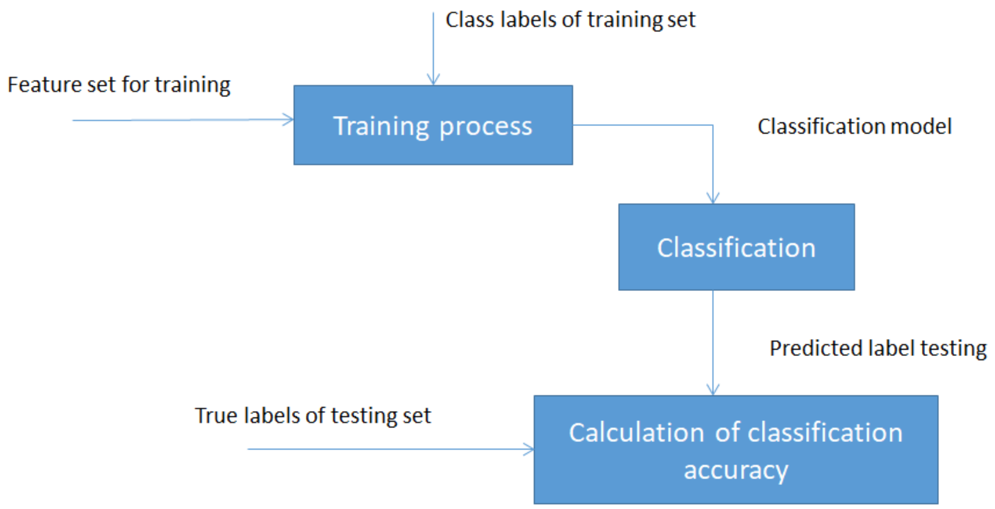

Figure 3.6: Classification mode

The accuracy for each case was calculated by :

$$Accuracy = \frac{Sum\ of(\ predicted\ labels)=test\ labels}{length\ of\ prediction\ lables} \tag{15}$$

Classifier level fusion was performed by combining posterior probabilities products from different classifiers. In the KNN classifier, the value of the nearest neighbor chosen was k=13 and Euclidean distance parameter was used for classification. In the SVM classifier, linear kernel function was used. The ANN network with an initial learning rate of 0.01 and a maximum of 50 epochs, was used for training. 10 input layers were used for neural network training. All the input features were standardized for training.

Chapter 4. Experimental Setup

In this chapter, we explain the setup used for collecting EEG data in this study for discriminating between genuine and acted expression. The participant description, the protocol of the experiment and description of stimuli is detailed in this section. Figure 4.1 shows the experimental setup. The electrode arrangement for the EEG cap used is given in the Figure 4.2.

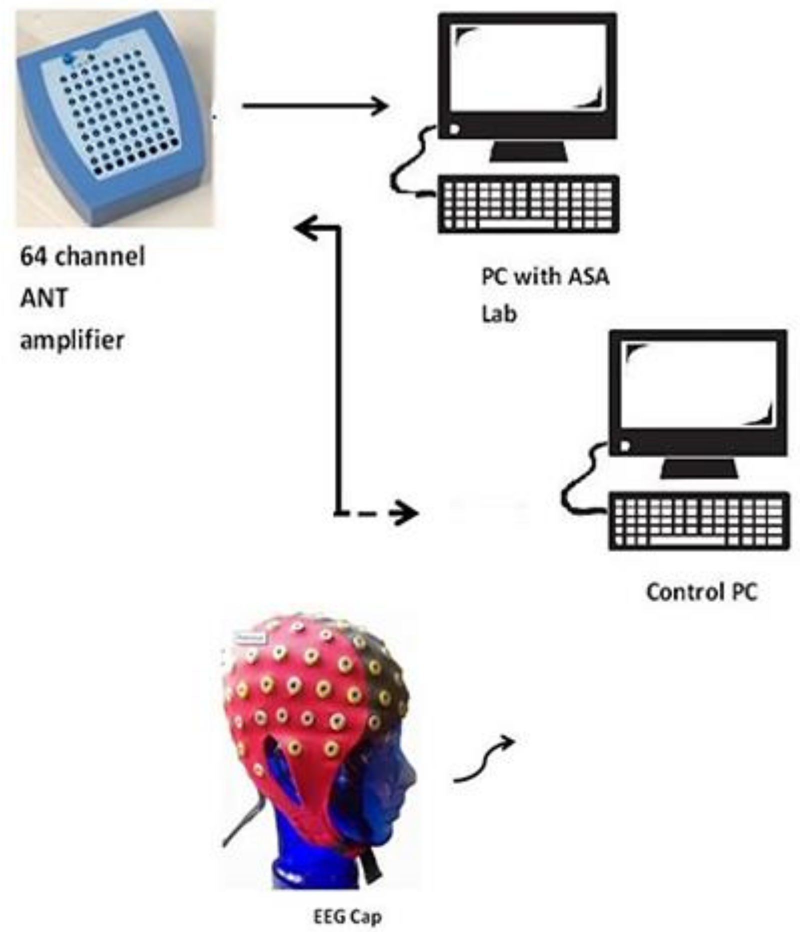

Figure 4.1: Experimental setup

4.1. Participants

28 healthy student subjects both female and male of age 19- 30 years with normal or corrected vision, on medication were recruited from the American University of Sharjah (AUS) to participate in this study. The study was approved by the

Institutional Review Board (IRB) of the American University of Sharjah. Written informed consent from every participant was obtained before the experiment.

4.2. Stimuli Description

Designs in emotion researches depend on successful emotion induction in the participants [30]. The protocol used in this study is shown in Figure 4.3. A total of 245 images will be used for this experiment. Out of which 70 images were neutral, 60 images were target book image (see Figure 4.4) and 115 images were positive funny images. All images were obtained from the online image database. The Geneva Affective Picture Database (GAPED) is a database of 730 pictures that were created to increase the availability of visual emotional stimuli. It contains four specific negative contents: spiders, snakes, and scenes that induce emotions related to violation of moral and legal norms (human rights violation or animal mistreatment). Positive and neutral pictures include: pictures that mainly represent human and animal babies as well as nature. The neutral pictures mainly depict inanimate objects. The pictures were rated according to valence, arousal. Valence and arousal scale, which were in turn used to rate emotions. Valence is in the range between positive and negative scale whereas arousal has a scale ranging from calm to active. Funny images had high arousal and valence. Neutral images had low arousal and valence and were chosen in a way to ensure that they did not evoke any emotion in the participant. Positive images had low arousal and high valence rating. They are presented in random order during the visual stimuli presentation. The target image for this experiment (a plain book) was a neutral image that did not evoke any emotions in the participant. When the target image appeared on the screen the participant had to pose an acted smile and hit a response key.

4.3. Data Collection

Data is collected under a controlled environment. 64-channel EEG data recorder was used in this experiment. The 10-20 system of the electrode placement was used for the data collection. EEG was amplified at 500 samples per second in the acquisition. Montages are logical and orderly arrangements of channels (electrode pairs), that display EEG activity over the entire scalp. The complete montage channel is listed in the Table 3.1.

Table 3.1: Montage channel listing

Waveguard 64 Amplifier Mapping

1	FP1	18	T8	35	AF4	52	P1
2	FPZ	19	A2	36	AF8	53	P2
3	FP2	20	CP5	37	F5	54	P6
4	F7	21	CP1	38	F1	55	PO5
5	F3	22	CP2	39	F2	56	PO3
6	Fz	23	CP6	40	F6	57	PO4
7	F4	24	P7	41	FC3	58	PO6
8	F8	25	P3	42	FCz	59	FT7
9	FC5	26	Pz	43	FC4	60	FT8
10	FC1	27	P4	44	C5	61	TP7
11	FC2	28	P8	45	C1	62	TP8
12	FC6	29	POz	46	C2	63	PO7
13	A1	30	O1	47	C6	64	PO8
14	T7	31	Oz	48	CP3	65	EOG
15	C3	32	O2	49	CPz	66	ECG
16	CZ	33	AF7	50	CP4	GND	AFz

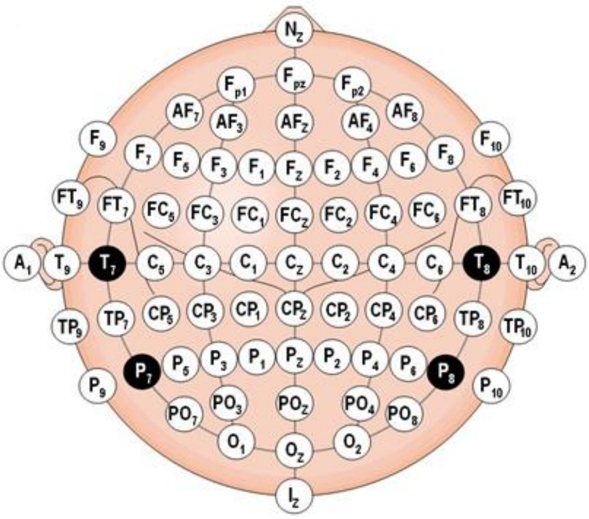

Figure 4.2: 10 -20 electrode placement

Asalab data acquisition software, version 4.9.2 and 4.9.3 (ANT B.V., Enschede, Netherlands) are used to record and analyse EEG data. Dell PC with 17-inch was used as the stimulus monitor. The control PC with SR Research software was used for stimulus presentation and to send event markers to EEG amplifier using a parallel port connection. The experiment was carried out in a quiet room with a controlled level of luminescence.

Before starting the experiment EEG data recording, several steps have to be completed. First, earlobes are cleaned with alcohol before wearing the EEG electrodes cap. The cap is adjusted manually to ensure that all electrodes are properly positioned in accordance with the 10-20 electrode system (see Figure.4.2). Then conductive electrode gel was filled using a dedicated syringe designed for this purpose. All electrodes had impedances below 10 KΩ. Some electrodes might be necessary to reduce the electrode's contact impedance to the desired value. After these preparation steps, the experiment begins. It lasted thirty minutes including 10 minutes preparation time.

4.4. Experiment Paradigm

The experimental paradigm is designed to test our hypothesis that recording the response for a genuine smile and target image for characterizing an acted smile. Figure.4.3 shows the protocol design used in this study.

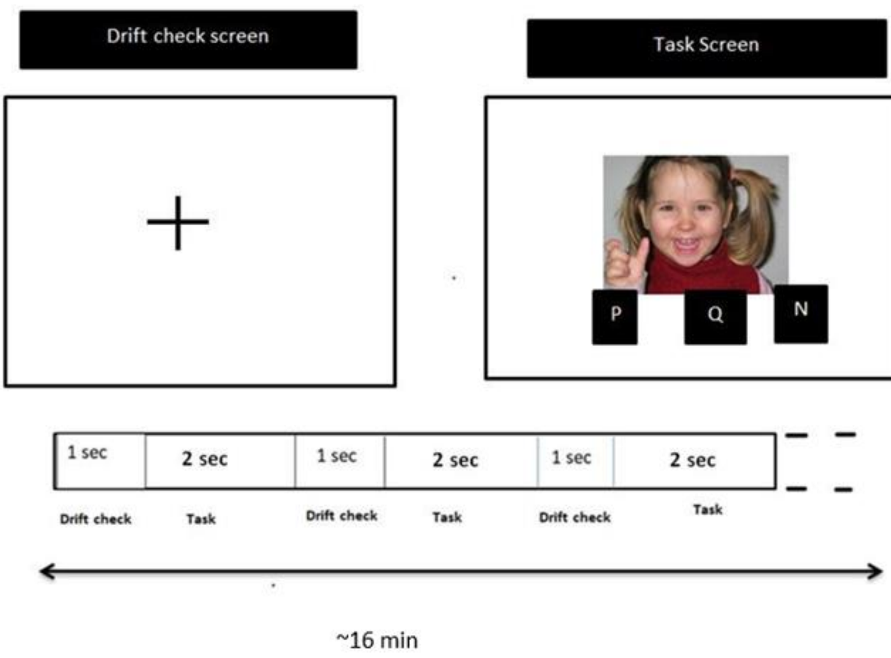

Figure 4.3: Experiment paradigm

The experiment begins with a display screen instruction to perform the experiment 3 seconds:

- Hit letter “ Q” for target image and pose an acted smile

The target image used for this study is shown in the Figure 4.4. This is a plain book cover image and hence will not any emotions in the participants.

Figure 4.4: Target image

- Hit letter “P” for the images that the participant found as funny and made them happy/excited feeling.
- Hit letter “N” for the images that the participant found as positive but no sort of excitement.

There are 246 trials in this experiment. Each trial begins with a drift check to ensure the focus is on the screen. This was followed by an image stimulus display. For every trial, an image is displayed on the screen for 3 seconds and the participant has to give a keyboard response by hitting any of the three letter keys. Also, a TTL signal is sent to the parallel port for EEG data recording upon the onset of image stimuli on the screen. The keyboard responses are then later used for labelling the epochs according to the three conditions.

Chapter 5. Results and Analysis

This chapter reports the results for the topographical maps across different conditions and classification performance. We also evaluated the performance of the two proposed feature extraction algorithms. This chapter contains two sections; the first section details the topographical plots and the second section describes the different classifier performances.

5.1. Power Distribution Topographies and Statistical Power Distribution Topographies

Figure 5.1 shows the averaged power distribution extracted using DWT from all subjects. The average power distribution was plotted on a normalized scale. The activation pattern of true and neutral emotions was much similar. However, the activation power of true emotion found in the left-frontal and central-parietal electrodes was higher in comparison to fake emotion. The statistical analysis was performed using a two-sample t-test. Figure 5.2 represents the topographical maps obtained from statistical t-test. True versus fake condition was statistically dominant compared to other cases. The observed trend was that the power was reducing from high frequency to low frequency. The prefrontal and right parietal/occipital regions held higher activation power in case 1 (true versus fake). The activation of the occipital region, in this case, may be due to the forceful smile. The power distribution decreased further in alpha and theta bands. In case 2 (true versus neutral), high activation power is observed in left cortical and parietal regions. In case3 (fake versus neutral smile), high-power activation was found in the central cortex regions only. The power distribution reduced while going from higher to lower frequencies. This is an indication that higher bands give better discrimination of the emotion. Thus, the results are consistent with previous studies [5], [6]. Figure 5.3 shows the topographies plotted using DWT-EMD method. The statistical analysis topographies using DWT-EMD method is also shown in Figure 5.4. The statistical significance increased on application of DWT-EMD technique. The red color is an indication that while performing the t-test the first condition was more dominant statistically over the other condition.

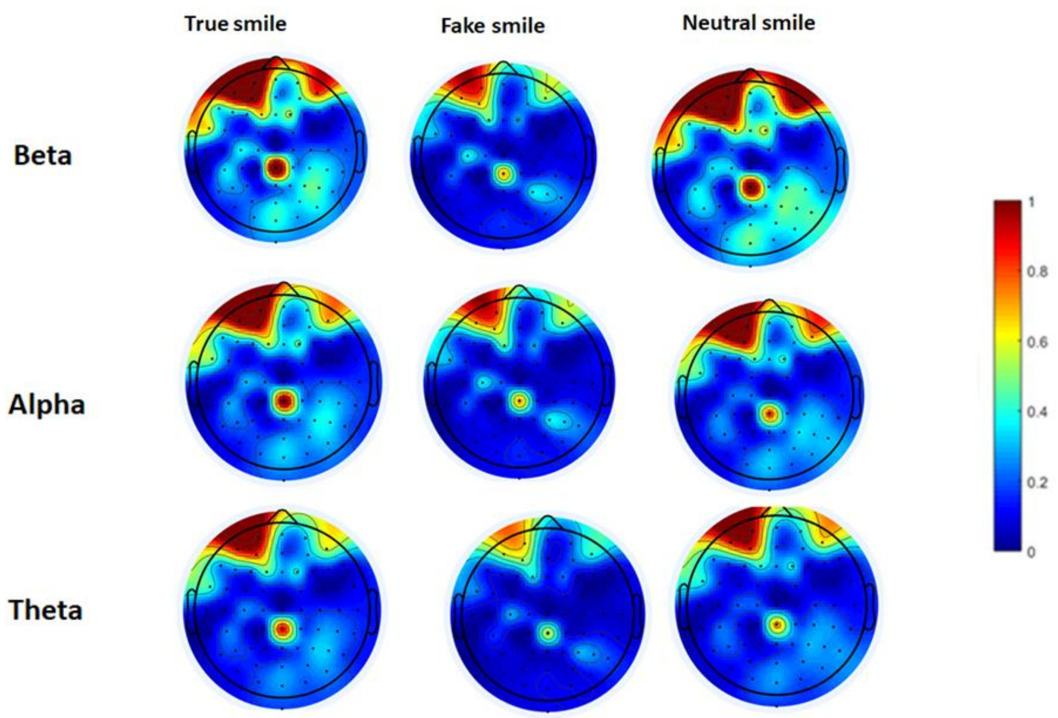

Figure 5.1: Power distribution topography using DWT method

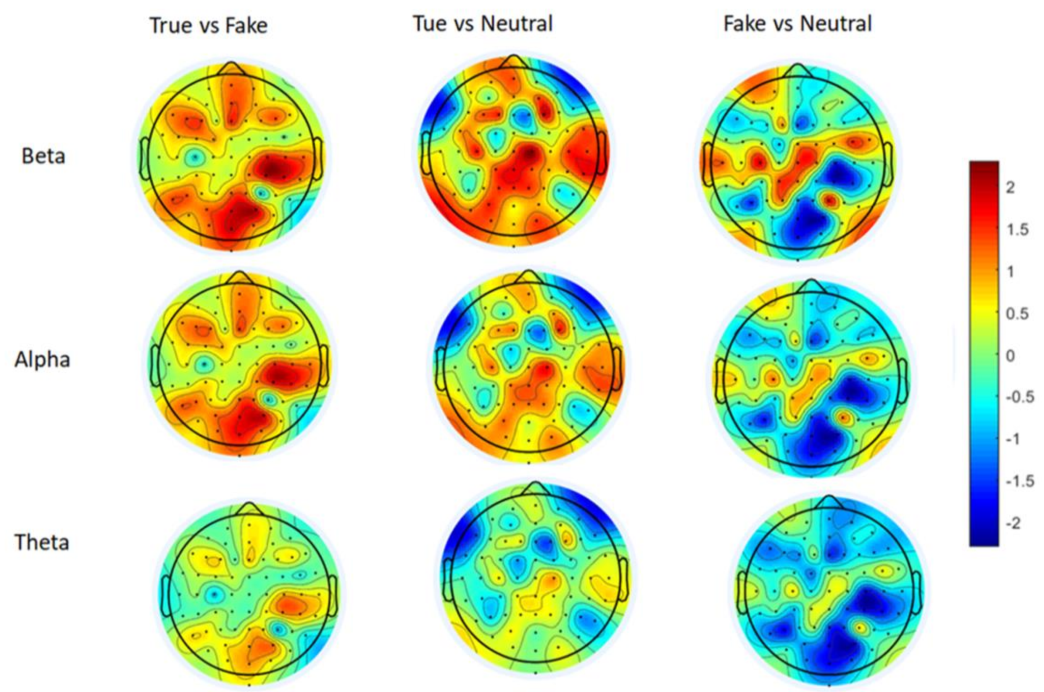

Figure 5.2: Statistical T-map topography of EEG rhythms

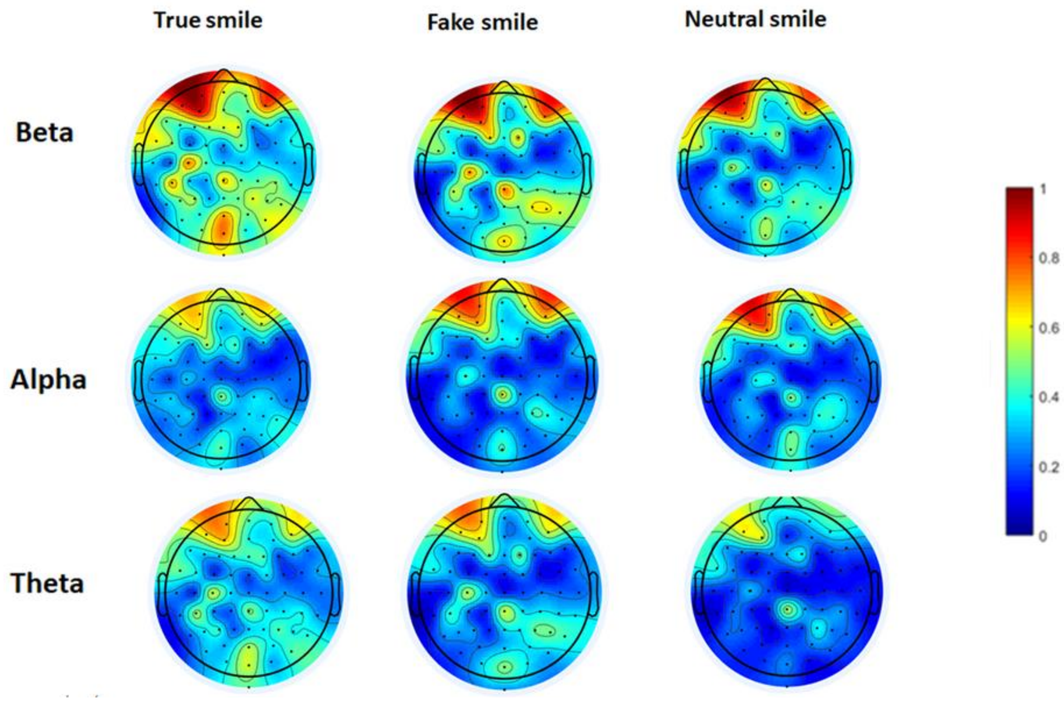

Figure 5.3: Power distribution topography using DWT-EMD method

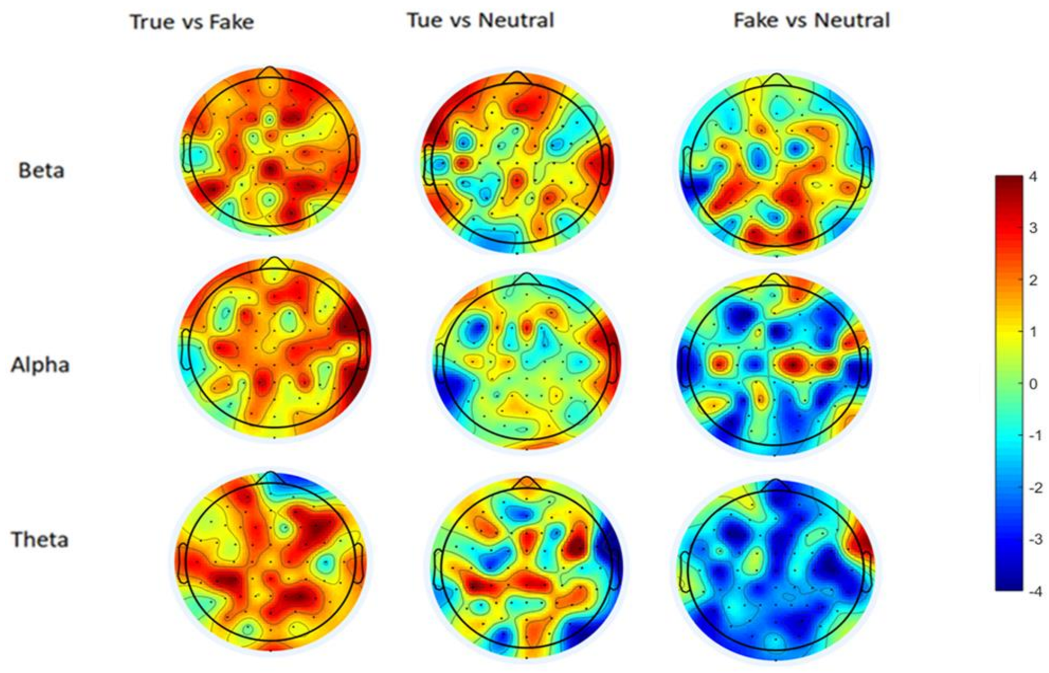

Figure 5.4: Statistical T-map topography of EEG rhythms

5.2. Classifier Performance Evaluation

In this section, the classification performance averages across all subjects are detailed. Averaged power distribution feature serves as the input to the classifier. There are three different classifiers used for this study: artificial neural network, k-nearest neighbour, and support vector machine. Classification performance from three frequency bands: beta, alpha, and theta are studied. A two-way classification across three frequency bands is also studied. To get an overall picture of classifier performance, classifier level fusion is applied. The following sections describe various classifier performances using the two different feature extraction method: discrete wavelet transform and discrete wavelet transform combined with empirical mode decomposition.

5.2.1. Classification performance using the DWT method. The average classification accuracy across subjects at various bands are shown in Figure 5.5, Figure 5.6, and Figure 5.7. Three cases have been considered namely: Case1: True versus Fake smile; Case 2: Fake versus Neutral smile and Case 3: True versus Neutral smile.

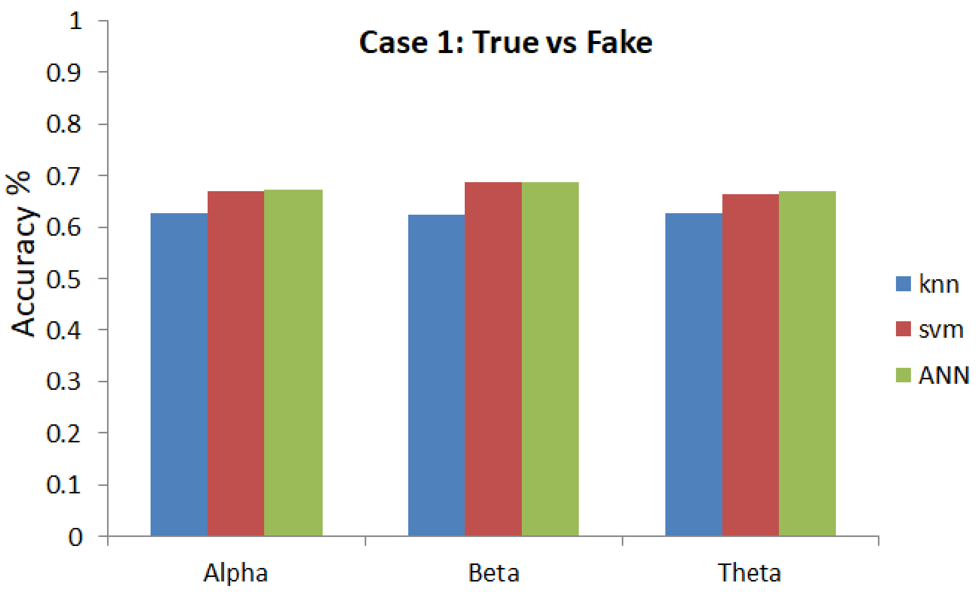

Figure 5.5: Case 1: Average classification accuracy across all subjects using ANN, KNN, and SVM classifiers.

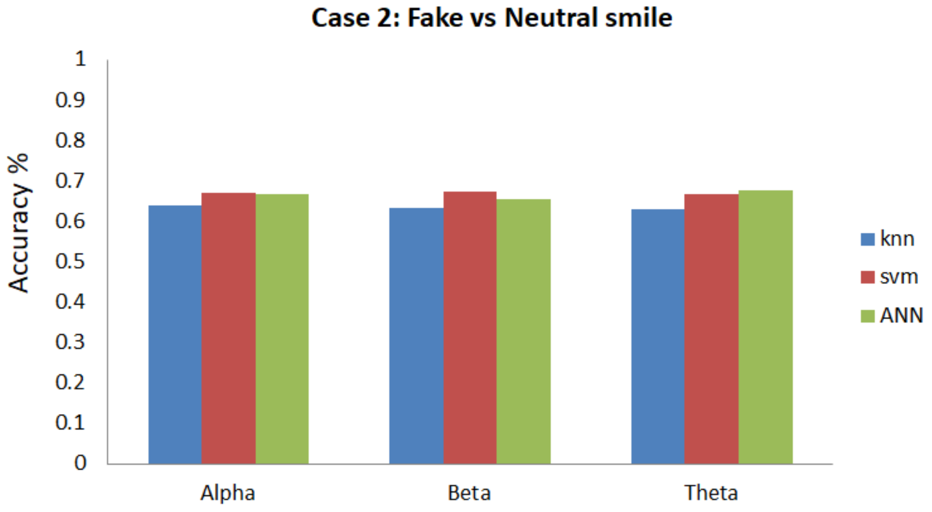

Figure 5.6: Case 2: Average classification accuracy across all subjects using ANN, KNN, and SVM classifiers.

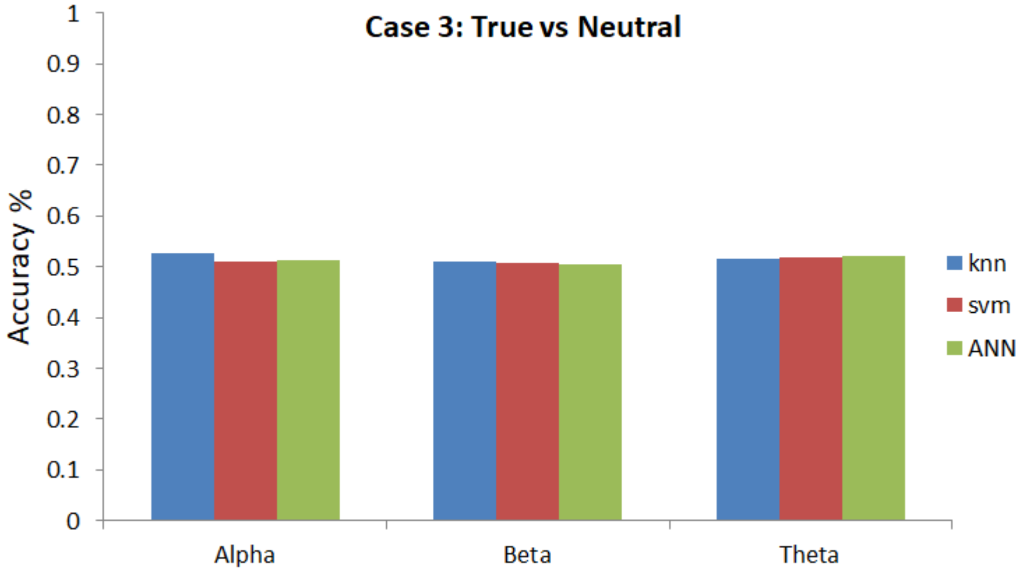

Figure 5.7: Case3: Average classification accuracy across all subjects using ANN, KNN, and SVM classifiers.

Figure 5.8 reports accuracy from the fusion of three classifiers: KNN, SVM, and ANN. The highest accuracy of 67.5 % was attained for the beta frequency band.

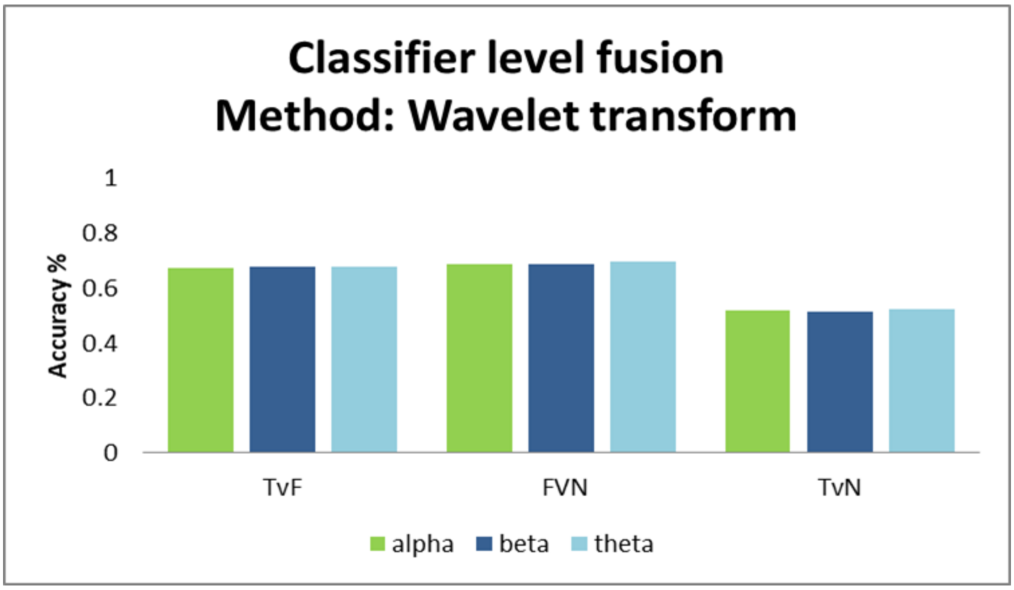

Figure 5.8: Average classification accuracy across all subjects by using classifier level fusion across the three bands

5.2.2. Classification performance using DWT-EMD method. The next step was to test the improvement in classification by involving empirical mode decomposition. Similar to the previous method two-way classification and performance on each of the band were evaluated. All three cases were tested as before. The following figures 5.9, 5.10, and 5.11 reports band wise classification accuracies across all the three cases. Fig. 5.12 shows the results of classifier level fusion across the three bands. The highest accuracy of 94.2 % was achieved in the alpha band for the True versus Fake case. Table 5.1 shows the comparison of the two methods reported in the tabular format. It is evident from these results that the higher band frequencies were able to classify the emotional expressions.

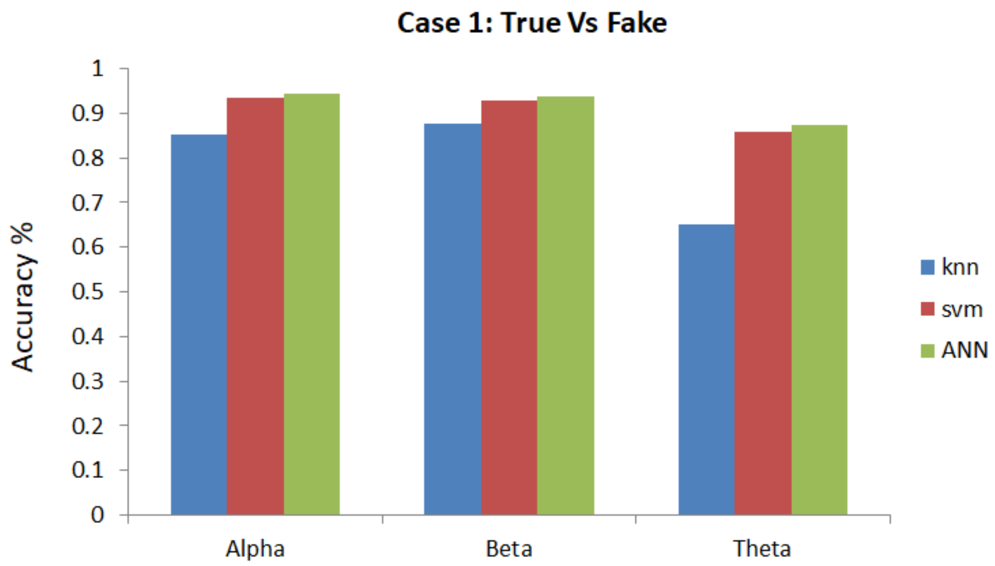

Figure 5.9: Case 1: Average classification accuracy across all subjects in the Alpha band using KNN, SVM, and ANN classifiers.

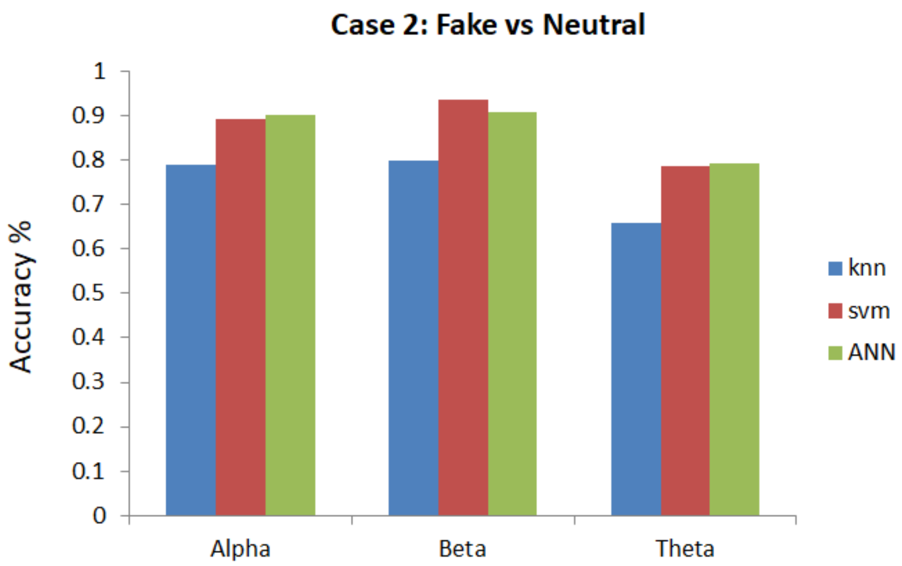

Figure 5.10 Case 2: Average classification accuracy across all subjects in the Alpha band using KNN, SVM and ANN classifiers.

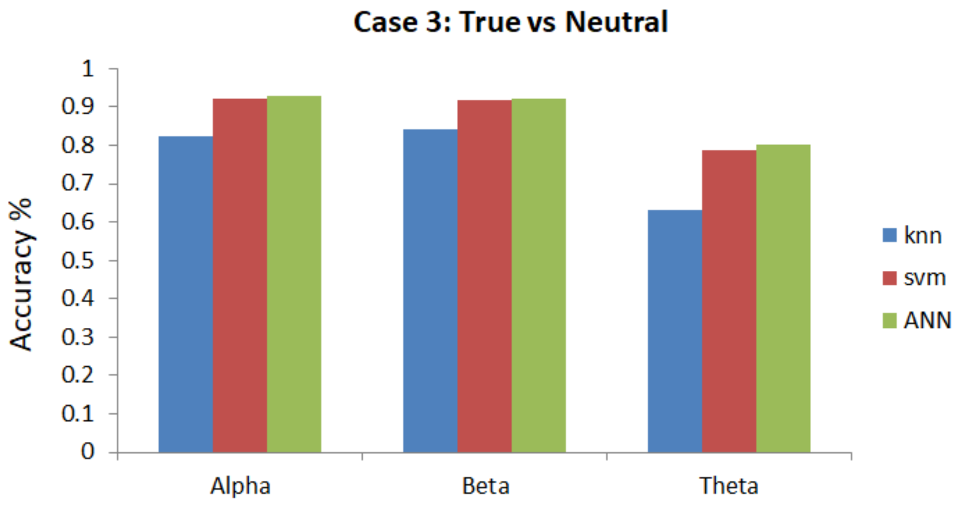

Figure 5.11: Case 3: Average classification accuracy across all subjects in the Alpha band using KNN, SVM, and ANN classifiers.

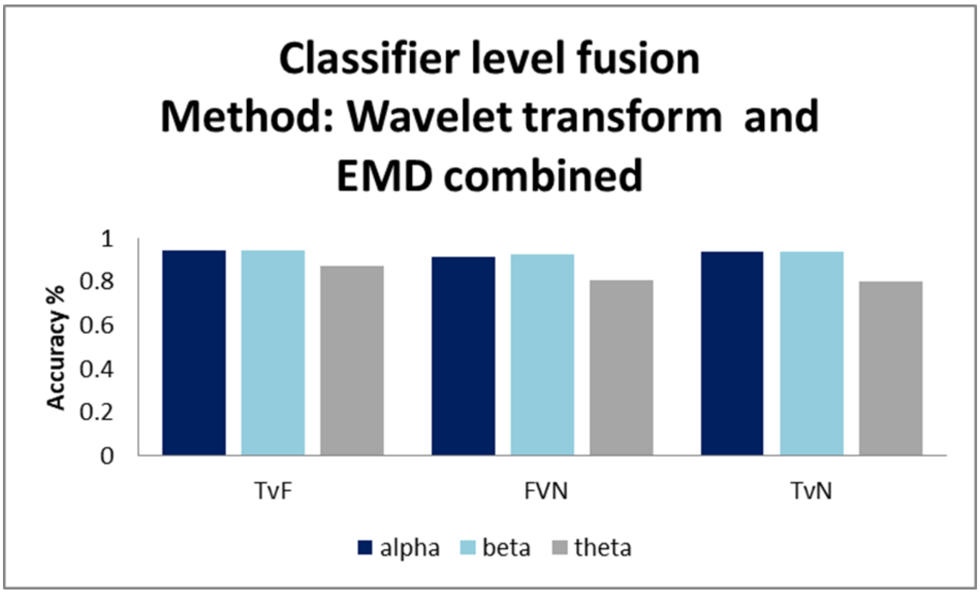

Figure 5.12: Average classification accuracy across all subjects by using classifier level fusion across the three bands

A comparison of the two-feature extraction is in the Table 5.1. The table results indicate that fusion of discrete wavelet transforms with empirical mode decomposition has substantially increased the classifier performance from 66.5 % to 94.2 % in the alpha band and from 67.5% 93.9 % in the beta band (true versus fake smile). And the highest possible accuracies were 94.2 % in the alpha band, 93.9% in the beta band and 86.9 % in the theta band.

Table 5.1: Comparison of classification accuracies using the two feature extraction methods

	DWT			DWT-EMD		
Frequency band	TvF	FVN	TvN	TvF	FVN	TvN
alpha	0.669	0.684	0.517	0.942	0.914	0.938
beta	0.675	0.684	0.512	0.939	0.924	0.936
theta	0.675	0.692	0.519	0.869	0.808	0.802

Chapter 6. Conclusion and Future Work

In this thesis, the method of emotion recognition has been used to distinguish between different emotional expressions: genuine smile acted smile and neutral smile. The results from the classification performance and statistical topography suggest that it is possible to differentiate between the three emotions from the EEG signal. Among the two-feature extraction methods employed, the DWT-EMD fusion method has yielded the highest classification accuracy in the higher frequency bands alpha and beta with 94.2% and 93.9% respectively. The significant increase in the classification accuracies by using this method suggests that incorporating EMD method has a high potential for in further emotion recognition studies. It can be observed that amongst all the classification cases the true versus fake smile cases has shown greater accuracies. This suggests that there are significant differences in the brains response towards expressing genuine and acted expressions which agree with the hypothesis of this thesis.

The experiment conducted in this emotion study had been done in a single session. However, the possibility of monitoring the stability of EEG responses over different sessions can be explored in later studies. Emotion-specific studies greatly rely on the choice of the emotional stimuli. In this study, we chose static images as visual stimuli. This helped in controlling of the beginning and end of every trial. Another major concern in data collection experiments is that they suffer from external interferences thereby corrupting the signal and this leading to loss of information. One of the best ways to get rid of this is by ensuring that the electrode caps are positioned in the correct way and impedance of all electrodes are set below 20 ohms. Thus, it can be concluded that two key factors in emotional monitoring experiments are emotion elicitation and reduction of artifacts at the time of recording. Reduction of the artifact is particularly important in emotion studies due to the fact that the brain's activation will be less compared to that can be observed in a cognitive experiment involving high mental input.

For future work, the performance of classifier by incorporating eye tracking data has can be analysed. The emotional correlations between the various eye gaze parameters like pupil dilations, and saccade velocity in response to positive and acted emotions can serve as a valuable source of information. This can also help in the development of remote devices in many applications involving human interactions. The future work can focus on comparing of the present dataset with other emotional databases. The brains behaviour with respect to its two hemispheres can be studied based on connectivity measures. This can help us in understanding the emotion correlation with respect to the right or left region in the brain. Deep learning techniques can also be applied to the same dataset. Since this emotion study has only focused on positive emotions, a well-defined emotional model can be developed for future comparison to other emotion-related studies. The application of DWT-EMD method on other types of emotions like sadness, amusement, etc. can be tested in further studies.

References

[1] H. Becker, J. Fleureau, P. Guillotel, F. Wendling, I. Merlet and L. Albera, "Emotion recognition based on high-resolution EEG recordings and reconstructed brain sources", *IEEE Transactions on Affective Computing*, pp. 1-1, 2017. Available: 10.1109/taffc.2017.2768030.

[2] S. Alarcao and M. Fonseca, "Emotions Recognition Using EEG Signals: A Survey", *IEEE Transactions on Affective Computing*, pp. 1-1, 2017. Available: 10.1109/taffc.2017.2714671.

[3] R. Alazrai, R. Homoud, H. Alwanni, and M. Daoud, "EEG-based emotion recognition using quadratic time-frequency distribution," *Sensors*, vol. 18, no. 8, pp. 2739, 2018.

[4] L.-C. Yu et al., "Building Chinese affective resources in valence-arousal dimensions," in *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 540-545,2016.

[5] W.-L. Zheng and B.-L. Lu, "Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks," *IEEE Transactions on Autonomous Mental Development*, vol. 7, no. 3, pp. 162-175, 2015.

[6] M. Teplan, "Fundamentals of EEG measurement," *Measurement Science Review*, vol. 2, no. 2, pp. 1-11, 2002.

[7] K. Blinowska and J. Zygierewicz, Practical biomedical signal analysis using MATLAB. *CRC Press*, 2011.

[8] N. E. Huang et al., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, vol. 454, no. 1971, pp. 903-995, 1998.

[9] E. Niedermeyer and F. L. da Silva, *Electroencephalography: basic principles, clinical applications, and related fields*. Lippincott Williams & Wilkins, 2005.

[10] G. C. Ribas, "The cerebral sulci and gyri," *Neurosurgical Focus*, vol. 28, no. 2, pp.2, 2010.

[11] Y.-Y. Lee and S. Hsieh, "Classifying different emotional states by means of EEG-based functional connectivity patterns," *PloS One*, vol. 9, no. 4, pp.95415, 2014.

[12] Y.-P. Lin et al., "EEG-based emotion recognition in music listening," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 7, pp. 1798-1806, 2010.

[13] H. Wang, A. Dragomir, N. I. Abbasi, J. Li, N. V. Thakor, and A. Bezerianos, "A novel real-time driving fatigue detection system based on wireless dry EEG," *Cognitive Neurodynamics*, pp. 1-12, 2018.

[14] M. Murugappan, M. Rizon, R. Nagarajan, S. Yaacob, I. Zunaidi, and D. Hazry, "EEG feature extraction for classifying emotions using FCM and FKM," *International Journal of Computers and Communications*, vol. 1, no. 2, pp. 21-25, 2007.

[15] D. R. Achanccaray and M. A. Meggiolaro, "Detection of artifacts from EEG data using wavelet transform, high-order statistics and neural networks," in *XVII Brazilian Conference on Automatica*, vol. 23,pp. 1-1,2008.

[16] E. S. H. Rooteh, Y. Zhang, and Z. Tian, "Comparison of parallel and single neural networks in heart arrhythmia detection by using ECG signal analysis," *Annual Confrence of the Prognostics and Health Management Society*, pp.1-1,2011.

[17] F. Al-Shargie, M. Kiguchi, N. Badruddin, S. C. Dass, A. F. M. Hani, and T. B. Tang, "Mental stress assessment using simultaneous measurement of EEG and fNIRS," *Biomedical Optics Express*, vol. 7, no. 10, pp. 3882-3898, 2016.

[18] G. Chanel, J. J. Kierkels, M. Soleymani, and T. Pun, "Short-term emotion assessment in a recall paradigm," *International Journal of Human-Computer Studies*, vol. 67, no. 8, pp. 607-627, 2009.

[19] B. J. Roach and D. H. Mathalon, "Event-related EEG time-frequency analysis: an overview of measures and an analysis of early gamma band phase locking in schizophrenia," *Schizophrenia Bulletin*, vol. 34, no. 5, pp. 907-926, 2008.

[20] N. E. Huang et al., "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, vol. 454, no. 1971, pp. 903-995, 1998.

[21] D.-x. Zhang, X.-p. Wu, and X.-j. Guo, "The EEG signal preprocessing based on empirical mode decomposition," *2nd International Conference on Bioinformatics and Biomedical Engineering*, pp. 2131-2134,2008.

[22] A. C. Yang, C.-K. Peng, and N. E. Huang, "Causal decomposition in the mutual causation system," *Nature Communications*, vol. 9, no. 1, pp. 3378, 2018.

[23] R. Munoz et al., "Using Black Hole Algorithm to Improve EEG-Based Emotion Recognition", *Computational Intelligence and Neuroscience*, vol. 2018, pp. 1-21, 2018. Available: 10.1155/2018/3050214.

[24] Q. Pinle, L. Yan, and C. Ming, "empirical mode decomposition method based on wavelet with translation invariance," *EURASIP Journal on Advances in Signal Processing*, vol. 2008, no. 1, pp. 526038, 2008.

[25] Z.-Q. Gong, M.-W. Zou, X.-Q. Gao, and W.-J. Dong, "On the difference between empirical mode decomposition and wavelet decomposition in the nonlinear time series," *Acta Physica Sinica*, no. 8 pp. 3957,2005.

[26] Z. Mohammadi, J. Frounchi, and M. Amiri, "Wavelet-based emotion recognition system using EEG signal," *Neural Computing and Applications*, vol. 28, no. 8, pp. 1985-1990, 2017.

[27] N. Zhuang, Y. Zeng, L. Tong, C. Zhang, H. Zhang and B. Yan, "Emotion Recognition from EEG Signals Using Multidimensional Information in EMD Domain", *BioMed Research International*, vol. 2017, pp. 1-9, 2017. Available: 10.1155/2017/8317357.

[28] S. K. Hadjidimitriou and L. J. Hadjileontiadis, "Toward an EEG-based recognition of music liking using time-frequency analysis," *IEEE Transactions on Biomedical Engineering*, vol. 59, no.12, pp. 3498-3510, 2012.

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

[30] R. M. Mehmood, R. Du, and H. J. Lee, "Optimal feature selection and deep learning ensembles method for emotion recognition from human brain EEG sensors," *IEEE Access*, vol. 5, pp. 14797-14806, 2017.

[31] M. Soleymani, S. Asghari-Esfeden, Y. Fu, and M. Pantic, "Analysis of EEG signals and facial expressions for continuous emotion detection," *IEEE Transactions on Affective Computing*, vol. 7, no. 1, pp. 17-28, 2016.

[32] H. Escola, E. Poiseau, M. Jobert, and P. Gaillard, "Classification using distance-based segmentation—application to the analysis of EEG signals," *Pattern Recognition Letters*, vol. 12, no. 6, pp. 327-333, 1991.

[33] O. Georgieva et al., "Learning to decode human emotions from event-related potentials," *Neural Computing and Applications*,vol.26,no.3,pp.573-580,2015.

[34] S. Liu et al., "Incorporation of Multiple-days Information to Improve the Generalization of EEG-based emotion recognition over time," *Frontiers in human neuroscience*,vol. 12, pp. 1-1,2018.

[35] W.-L. Zheng, B.-N. Dong, and B.-L. Lu, "Multimodal emotion recognition using EEG and eye tracking data," 3*6th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 5040-5043,2014.

[36] Y. Zhang, X. Ji, and S. J. N. l. Zhang, "An approach to EEG-based emotion recognition using combined feature extraction method," *Neuroscience letters*,vol. 633, pp. 152-157, 2016.

[37] X. Li, D. Song, P. Zhang, Y. Zhang, Y. Hou, and B. J. F. i. n. Hu, "Exploring EEG features in cross-subject emotion recognition," *Frontiers in human neuroscience*,vol. 12, pp. 162, 2018.

[38] Y. Zhang, S. Zhang, X. J. M. T. Ji, and Applications, "EEG-based classification of emotions using empirical mode decomposition and autoregressive model," *Multimedia Tools and Applications*,vol. 77, no. 20, pp. 26697-26710, 2018.

Vita

Meera Alex was born in 1993, in Kerala, India. She received her B.Sc. degree in Biomedical Engineering from the Calicult University in 2015. From 2015 to 2016, she worked as a trainee Biomedical engineer in Tawam hospital under SEHA.

In August 2017, she joined the Biomedical Engineering master's program in the American University of Sharjah as a graduate teaching assistant. Her research interests are in Neuro-engineering research field.