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Using minimal number of electrodes for emotion detection using noisy EEG data

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USING MINIMAL NUMBER OF ELECTRODES FOR EMOTION DETECTION USING NOISY EEG DATA

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Abstract

Emotion is an important aspect in the interaction between humans. It is fundamental to human experience and rational decision-making. There is a great interest for detecting emotions automatically. A number of techniques have been employed for this purpose using channels such as voice and facial expressions. However, these channels are not very accurate and can be faked. Other techniques use physiological signals along with electroencephalography (EEG) for emotion detection. However, these approaches are not very practical for real time applications because they ask the participants to reduce any motion and facial muscle movement, reject EEG data contaminated with artifacts and rely on large number of electrodes. In this thesis, we propose an approach that analyzes highly contaminated EEG data produced from a new emotion elicitation technique. We also use a feature selection mechanism to extract features that are relevant to the emotion detection task based on neuroscience findings.

Our main contribution is in the experimental methodology applied for building an automated system for emotion detection. First we experimented with a totally new emotion elicitation technique that is very close to real life situations. Second, We generate different feature sets from the prior art and compare the accuracies of different classifiers that use such different feature sets. We experimented with two feature sets that are based on some neuroscience findings. The first neuroscience fact is based on the finding the that emotions are most obvious in the alpha band which ranges from 7 to 13 Hz [1]. The second neuroscience finding is that positive emotions result in relatively greater left brain activity and negative emotions result in greater right brain activity. Hence, we decided to focus our experiments on the alpha band and making use of scalp asymmetries in case of positive and negative emotions. Finally, we experimented with different number of electrodes that were selected using two different methodologies. The first approach is to include the frontal electrodes because the alpha rhythm is most obvious in the frontal lobe. The second approach is not to include any frontal electrodes because EMG artifacts may contaminate the frontal lobe and we want to make sure that our classification results are mainly due to EEG and not EMG.

Our work extends existing research in four principal ways. First, we are the first in the computer science field to use voluntary facial expression as a means for enticing emotions.

Although this contaminates EEG with noise, it helps to test our approach on unconstrained environment where the users were not given any special instructions about reducing head motions or facial expressions which makes our dataset close to a real time application. Second, we used a new technique for selecting features that are relevant to the emotion detection task that is based on neuroscience findings. Third, since one of the drawbacks of emotion detection systems using EEG is the use of large number of electrodes, which hinders the portability of such systems, we applied our approach on different number of electrodes that range from 4 electrodes up to 25 electrodes using two methodologies for selecting the electrodes to be eliminated. This can make our system more portable and can be used in real application. Finally, we tested our approach on a large dataset of 36 subjects and we were able to differentiate between four different emotions with an accuracy that ranges from 51% to 61% using 25 electrodes and we reached an average classification accuracy of 33% for joy emotion, 38% for anger, 33% for fear and 37.5% for sadness using 4 or 6 electrodes only.

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Acknowledgments

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Chapter 1

Introduction

An emotion is a mental and physiological state associated with a wide variety of feelings, thoughts, and behavior. An emotion is a subjective experience which makes studying emotions one of the most confused and still open fields of research in psychology [2]. There are more than 90 definitions of "emotion" and there is little consensus on the meaning of the term. The reason why studying emotions is important is the fact that emotion is an important aspect in the interaction between humans. Emotion is fundamental to human experience, influencing cognition, perception, and everyday tasks such as learning, communication, and even rational decision-making.

There are two models for theoretical emotion representation. The first model that is proposed by Darwin [3] and followed after that by Plutchik [2] and Ekman [4], uses the idea that all emotions can be composed of some basic emotions exactly like the white color can be composed of primary colors. Plutchik [2] claims that there are eight basic emotions which all other emotions can be derived from. These eight emotions are anger, fear, sadness, disgust, surprise, curiosity, acceptance and joy. Ekman [4] has chosen other emotions to be the basic emotions. He considered anger, fear, sadness, happiness, disgust and surprise as the basic emotions.

The second model as shown in Fig. 1.1 [5] used to represent emotion is the dimensional view model [6]. It describes each emotion on a multidimensional scale. The first dimension is emotional valence, with positive emotions on one side and negative emotions on the other side. The second dimension represents the arousal. Sometimes, there is a third dimension which represents dominance. However, it is rarely used. The second model is used in most of the studies because of its simplicity and universality and there is little controversy

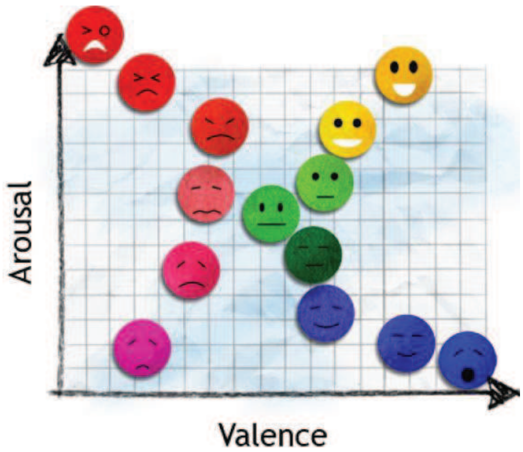

Figure 1.1: Two dimensional view of emotion [7].

about the two dimensions of the model.

There are a lot of studies to capture emotions automatically. Developing systems and devices that can capture and process human emotions and making use of them is the purpose of affective computing. Affective computing is related to, arise from or influence emotion or other affective phenomena [8]. It is an interdisciplinary field that requires knowledge in psychology, computer science and cognitive sciences.

Affective computing and emotion assessment are now growing fields because they have many potential applications. For instance, emotion assessment can be integrated in human-computer interaction systems that will lead to improve these systems by making them get close to human-human interaction. This will enhance the usability of the systems and improve the quality of life of disabled people who find difficulty in using the interfaces provided to healthy people. Another type of emerging applications that make use of capturing users' emotions is quantifying customers' experience. These types of applications require an automated system to deduct customers' emotions without having them state it explicitly.

Quantifying customers' experience using machine-aided techniques is becoming of great interest to many companies. These companies often conduct market research to build market share, competitive advantage and to predict how people would like their product. The problem with predicting customer's experience is that the current evaluation methods such as relying on customers' self reports are very subjective.

People are not always feeling comfortable revealing their true emotions. They may inflate their degree of happiness or satisfaction in self reports. Participants report higher well-being in face-to-face interviews than they do in mail surveys or self-administered questionnaires [9]. This is because participants are unwilling to reveal their true emotions to strangers. In case of interviews, this interviewer effect disappears when the interviewer is severely handicapped [10]. Participants would like to give positive feelings to others but would rather not exaggerate when faced with another's unfortunate situation. This can show that self reports are very subjective and affected by external factors. Due to the inaccuracy of self reports, market researchers are trying to find new channels by which they can capture the users' affective states without asking them for their direct opinion.

Another type of important applications is helping people who suffer from psychological problems to interact and communicate easily with computers and humans by capturing the person's emotion and make the system self adapt based on the user's current emotion. For instance, people who are suffering from autism have difficulty in interacting with others in social environment. An affective computing system can provide solution to those people. One of these systems proposed in [11] captures the emotions of people interacting with the person suffering from Asperger Syndrome, autistic spectrum. It then gives an advice to the autistic patient of a good response.

Affective computing helps people to better interact with machines and computers and have a wide variety of applications. The success of an affective computing or an emotion assessment system is mainly based on the accuracy of detecting emotions from expressive human channels. These expressive channels include facial expressions, voice and electroencephalography (EEG). Affective computing, coupled with new wearable computers, will also provide the ability to gather new data necessary for advances in emotion and cognition theory [8].

There are two main approaches for eliciting participants' emotions. The first method presents provoking auditory or visual stimulus to elicit specific emotions. This method is used by almost all studies in literature [12–18]. The second approach builds on the facial feedback paradigm which shows that facial expressions are robust elicitors of emotional experiences. In the famous Strack, Martin & Stepper's study [19], Strack, Martin & Stepper attempted to provide a clear assessment of the theory that voluntary facial expressions can result in an emotion. Strack, Martin, & Stepper [19] devised a cover story that would ensure the participants adopt the desired facial posing without being able to perceive either the corresponding emotion or the researchers' real motive. Each participant was asked to hold a pen in his mouth in different ways that result in different facial poses.

Participants who held a pen resulting in a smile reported a more positive experience than those who held the pen in a position that resulted in a frown. This study was followed by different psychologists including Ekman et al. [20] who found that emotions generated with a directed facial action task results in a finer distinction between emotions. However, this approach contaminates brain signals with facial muscle artifacts and that's why this approach is not conceived by computer scientists.

1.1 Emotion Detection Channels

There is much work done in the field of emotion and cognitive state detection by analyzing facial expressions or/and speech. Some of these systems showed a lot of success such as those discussed in [21] [22]. The system proposed in [21] uses an automated inference of cognitive mental states from observed facial expressions and head gestures in video. The system is based on a multilevel dynamic Bayesian network classifier which models cognitive mental states as a number of interacting facial and head displays. The system proposed in [22] makes use of multimodal fusion of different timescale features of the speech. They also, make use of the meaning of the words to infer both the angry and neutral emotions. Although facial and voice expressions are considered to be a very powerful means for humans to communicate their emotions [3], the main drawback of using facial expressions or speech is the fact that they are not reliable indicators of emotion because they can either be faked by the user or may not be produced as a result of the emotion.

The other alternative for emotion and cognitive state detection is analyzing physiological signals because they are not experiencing the same drawback of video and speech. These types of signals cannot be faked due to the fact that they are produced from some involuntary secretion glands as a result of specific stimulus. Some of the systems that rely on detecting physiological signals make use of the signals generated from the peripheral nervous system such as skin temperature variation, heart rate, blood pressure and skin conductance. One of the systems that was able to classify four different emotions, anger, sadness, stress and surprise, is proposed by Kim et al. [12]. In this system, Kim et al. [12] made use of ECG and body temperature to recognize the four emotions. They tested their hypothesis on large dataset generated from 50 subjects and were able to reach an accuracy of 78.4% and 61.8% for three and four emotion categories respectively.

Based on the cognitive theory of emotion, the brain is the center of every human

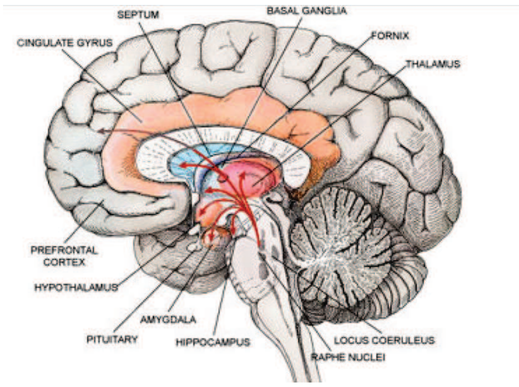

Figure 1.2: Different parts of the human brain

action [13]. Consequently, emotions and cognitive states can be detected through analyzing physiological signals that are generated from the central nervous system such as EEG signals. However, there is little work done in this area of research. Thanks to the success of brain computer interface systems, a few new studies have been done to find the correlation between different emotions and brain signals.

1.2 Emotions and the Human Brain

Some of the brain structures play an important role in the emotional brain. The different parts of the brain are shown in Fig. 2.3. Some of these structures are:

1.2.1 Amygdala

The amygdalae is considered to be one of the most important regions of the brain that are related to emotions. It is composed of two groups of neurons deep inside the human brain. Whenever a person receives some emotional load, the amygdala is the part of the brain that recognizes this emotional load. Amygdala is also responsible for long term emotional memories. Also, the amygdala is responsible for learning the connections between some stimulus and a threatening events [7].

1.2.2 Hypothalamus

The hypothalamus is the part of the brain that controls visceral functions in the body such as body temperature, hunger and thirst. It is also responsible for certain responses such as feeding, drinking and is involved in processing emotions and sexual arousal [7].

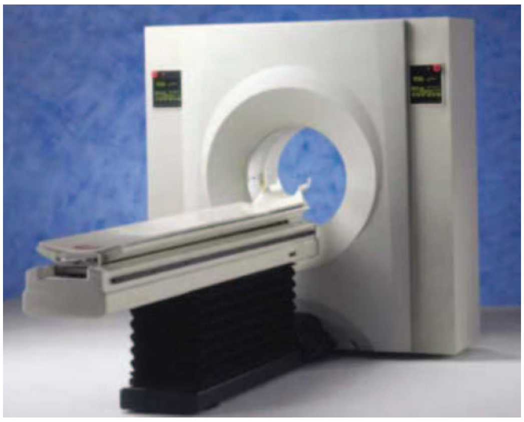

Figure 1.3: Positron Emission Tomography scanning system. Image from www.radiologyinfo.org

1.2.3 Prefrontal cortex

The prefrontal cortex (PFC) plays a role in reward processing. Neurons in the PFC can detect changes in the reward value of learned stimuli. Furthermore, the PFC is involved in planning, making decisions based on earlier experiences and working towards a goal. The combination of functions of the PFC is described as the executive function [7].

1.2.4 Anterior cingulate cortex

This part of the brain is generally subdivided into a cognitive and an affective part. The affective part is suggested to monitor disagreement between the functional state of the organism and any new information, that might have affective consequences [7].

1.2.5 Insular cortex

The insular cortex is said to be associated with emotional experience and produces conscious feelings. It combines sensory stimuli to create a emotional context [7].

1.3 Methods for Measuring Brain Activity

As mentioned, the brain is the center of every human action [13]. Different technologies have been developed for measuring the brain activity. The most commonly used techniques are positron emission tomography (PET), functional magnetic resonance imaging (FMRI) and electroencephalography (EEG).

Figure 1.4: Functional Magnetic Resonance Imaging scanning system. Image from www.ftcm.org.uk

1.3.1 Positron Emission Tomography (PET)

Positron Emission Tomography (PET) is a technique for measuring the brain activity. It is a type of radiation during which a radioactive isotope is injected into someone's blood. The isotope emits positrons which are taken with the blood flow. The blood flow is correlated with brain activity. The machine shown in Fig. 1.3 can show the blood flow given the presence of positrons.

One advantage of PET is its high spatial resolution. However, there are three main disadvantages for this approach. First, it has a very low time resolution and time delay due to the time taken before the radioactive material arrives the brain. Second, this methodology requires the person being subjected to a radiation which may not be very safe for long time. Finally, it requires huge expensive devices which hinders the possibility of using such approach in real life situations.

1.3.2 Functional Magnetic Resonance Imaging (FMRI)

Functional magnetic resonance imaging (FMRI) is another method that depends on the blood flow. As mentioned before, blood flow is correlated with brain activity. This is because active neurons consume oxygen that is carried by the blood hemoglobin. This consumption of oxygen changes the magnetic properties of hemoglobin, and these magnetic properties are measured by the FMRI system shown in Fig. 1.4. FMRI shares the same advantages and disadvantages of PET. Both have high spatial resolution but low temporal resolution. FMRI also requires huge expensive hardware which makes it impractical for applications in real life situations.

Figure 1.5: EEG cap and electrodes.

1.3.3 Electroencephalography (EEG)

Electroencephalography (EEG) uses the electrical activity of the neurons inside the brain. When the neurons are active, they produce an electrical potential. The combination of this electrical potential of groups of neurons can be measured outside the skull, which is done by EEG. Because there is some tissue and even the skull itself between the neurons and the electrodes, it is not possible to measure the exact location of the activity.

In order to record brain signals using EEG, a cap and electrodes as shown in Fig. 1.5 are used. The main advantage of using EEG is its portability and relatively inexpensive hardware. However, it has low spatial resolution. That's why researchers usually use huge number of electrodes that are placed all over the scalp to overcome this drawback.

Most of the studies that tries to capture the user's emotional state from the brain signals combine both EEG signals with other physiological signals generated from the peripheral nervous system [14] [15]. Although using both modalities require using large number of electrodes scattered all over the body, it is done to provide better classification accuracies. However, in this research, we will focus on inferring emotion from EEG signals only because we are interested in a portable convenient approach with the least possible number of electrodes.

1.4 Problem Definition

There is a great interest in developing automated systems for emotion detection. A lot of emerging applications can rely on an accurate systems for emotion detection to achieve their goal. These application include software adaptation, quantifying customers' experience for product evaluation, building assistive technologies and monitoring safety critical systems.

A number of techniques have been employed for building automated systems for emotion detection. These techniques included using channels such as voice and facial expressions. However, these channels are not very accurate because they can be affected by users' intentions and they can be faked. Other techniques use physiological signals that are produced from the peripheral nervous system such as heart beat, body temperature and blood pressure. Although these signals cannot be faked, it requires the use of large number of sensors that are scattered all over the body. This makes such approach neither convenient nor portable for usage in real life situations.

Finally, current approaches for emotion detection using EEG are not very practical for real life situations because the researchers either ask the participants to reduce any motion and facial muscle movement or reject EEG data contaminated with artifacts. Also, their approaches rely on using large number of electrodes which makes such systems not portable.

1.5 Research Objective

Instead of using a visual or an auditory stimulus for emotion elicitation, we decided to use voluntary facial expression based on the facial feedback paradigm which shows that facial expressions are robust elicitors of emotional experience, as a means for eliciting emotions. The reason we chose to use this elicitation technique is that although it contaminates EEG with noise, it helps to test our approach on unconstrained environment where the users will not be given any special instructions about reducing head motions or facial expressions.

We were also interested in using different ways for selecting features that are relevant to the emotion detection task that is based on two main neuroscience findings. The first neuroscience finding is the fact that emotions are most obvious in the alpha band which ranges from 7 to 13 Hz [1]. The second neuroscience finding is that positive emotions result in relatively greater left brain activity and negative emotions result in greater right brain activity. So we decided to focus our experiments on the alpha band and making use of scalp asymmetries in case of positive and negative emotions.

Finally, since one of the drawbacks of the current emotion detection using EEG work is the use of large number of electrodes which hinders the portability of such systems, we applied our approach on different number of electrodes that range from 4 to 25 electrodes. This can make our system more portable and can be used in real applications. Our goal was to reach a reasonable accuracy with the fewest number of electrodes.

This thesis is organized as follows: chapter 2 gives an introduction about electroencephalography, the different brain rhythmic activities and the types of artifacts that contaminate brain signals. Chapter 3 surveys related work on different channels used for emotion detection, especially those that use EEG. Chapter 4 gives an overview of our methodology for emotion detection using EEG. Experimental evaluation and results are presented in chapter 5. Chapter 6 concludes the paper and outlines future directions in the area of emotion detection using EEG.

Chapter 2

Electroencephalogram Primer

Electroencephalography (EEG) is a method used in measuring the electrical activity of the brain from the cerebral cortex. This activity is generated by billions of nerve cells, called neurons. Each neuron is connected to thousands of other neurons. When this sum exceeds a certain potential level, the neuron fires nerve impulse. The electrical activity of a single neuron cannot be measured with scalp EEG. However, EEG can measure the combined electrical activity of millions of neurons [23].

There are two approaches for capturing EEG signals which differ in the brain layer where the electrodes are placed to capture the signals. The first approach is the invasive approach. In which very small electrodes are implanted directly over the cortex during neurosurgery as shown in the Fig. 2.1. The advantage of this approach is that it gives a very high quality EEG signals. However, it requires surgical operation.

The other approach is the non invasive approach in which electrodes are placed on the surface of the scalp as shown in the Fig. 2.2. The problem with non invasive EEG recording is the poor quality of the signals because the skull dampens the signals, dispersing and

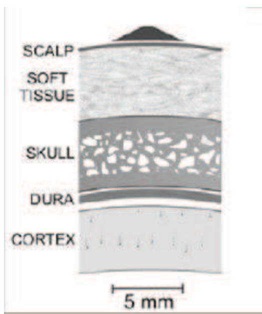

Figure 2.1: Invasive BCI. The electrode is implanted directly over the cortex.

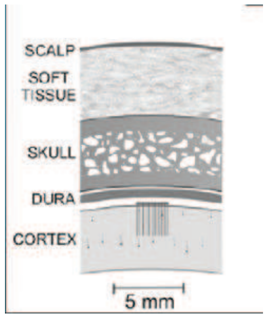

Figure 2.2: Noninvasive BCI. The electrodes capture the signals from the surface of the scalp.

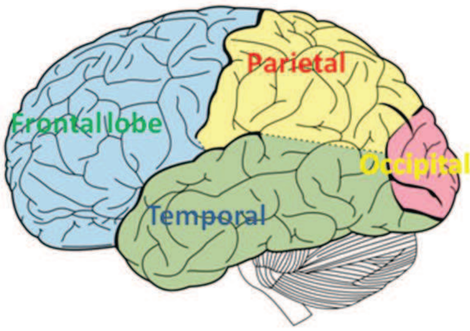

Figure 2.3: Different parts of the human brain.

blurring the electromagnetic waves created by the neurons. Another problem of the non invasive approach is that it has a low spatial resolution. It is very difficult to determine the area of the brain that created them or the actions of individual neurons. Almost all today's EEG recordings are done non-invasively.

The semantic of the EEG signal depends mainly on the places where the signals are captured. Each part of the brain has its own function. The brain has four main areas as shown in the Fig. 2.3. The frontal lobe is responsible for body limb movements and facial muscle movements. The parietal region is responsible for sensory information such as taste, pressure, sound and temperature. The occipital region is the center of visual processing. Finally, the temporal region is the center of auditory processing.

In order to allow EEG recordings performed in one laboratory be interpreted in another, the 10-20 system, an international system of electrode placement, was introduced during the 1950s. This system utilizes several distinctive landmarks to help researchers capture EEG related to the tasks of interest. A top view is shown in the Fig 2.4.

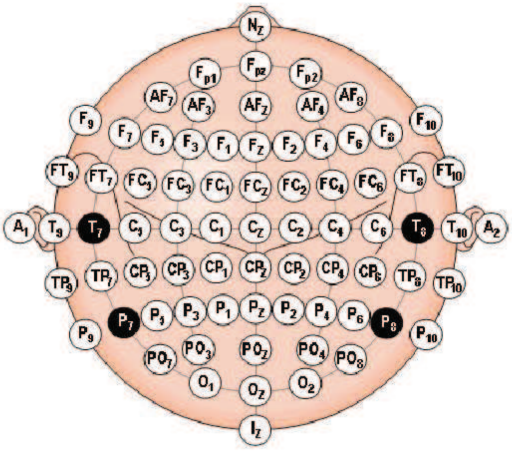

Figure 2.4: A top view of the brain that shows the locations for EEG recording according to the 10-20 system.

Table 2.1: Different EEG Rhythms

Rhythm	Frequency Range	Location	Reason
Delta	(0-4) Hz	Frontal lobe	Deep sleep
Theta	(4-7) Hz	Midline, temporal	Drowsiness and meditation
Alpha	(8-13) Hz	Frontal, Occipital	Relaxing, closed eyes
Mu	(8-12) Hz	Central	Contralateral Motor acts
Beta	(13-30) Hz	Frontal, central	Concentration and thinking
Gamma	(30- 100+) Hz		Cognitive functions

2.1 Rhythmic Activity

EEG can be described in terms of the signal rhythmic activity. This rhythmic activity can be divided into number of bands that differ in the range of the frequency they cover. Table 2.1 gives an overview on the different rhythmic bands, their frequency range, the brain location where they are most obvious and the reason why these signals are generated.

2.2 EEG Artifacts

One of the main problems that affect the accuracy of processing EEG is the large contamination of the signals with artifacts. There are two main sources of noise that may contaminate the recorded EEG signal which are technical artifacts and physiological artifacts.

The technical artifacts are usually related to the environment where the signals are captured. One source of technical noise is the electrodes itself. if the electrodes are not properly placed over the surface of the scalp or if the resistance between the electrode and the surface of the scalp exceeds 5 kohm, this will result in huge contamination of the EEG. Another source of technical artifact is the line noise. This noise occurs due to A/C power

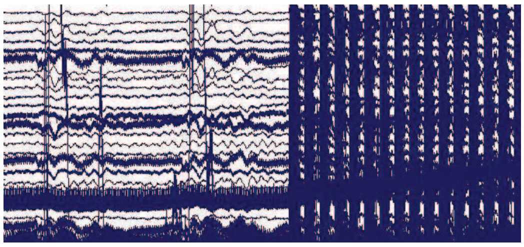

Figure 2.5: Contaminated EEG signal with line noise.

supplies which may contaminate the signal with 50/60 Hz if the acquisition electrodes are not properly grounded. An example of the shape of EEG contaminated with line noise can be shown in Fig. 2.5.

Another sources of noise are the physiological artifacts. Physiological artifacts are related to the subject undergoing the EEG recording. Those physiological artifacts include eye blinking, eye movements, Electromyography (EMG), motion, pulse and sweat artifacts. The problem in eye blinking is that it produces a signal with a very high amplitude that is usually much greater than the amplitude of the EEG signals of interest. Eye movements are similar to or even stronger than eye blinks. The EMG or muscle activation artifact can happen due to some muscle activity such as movement of the neck or some facial muscles. This can affect the data coming from some electrodes, depending on the location of the moving muscles. As for the motion artifact, it takes place if the subject is moving while EEG is being recorded. The data obtained can be corrupted due to the signals produced while the person is moving, or due to the possible movement of electrodes. Another involuntary types of artifacts are pulse and sweat artifacts. The heart is continuously beating causing the vessels to expand and contract; so if the electrodes are placed near blood vessels, the data coming from them will be affected by the heart beat. Sweat artifacts can affect the impedance of the electrodes used in recording the brain activity. Subsequently, the data recorded can be noisy or corrupted.

These different types of noise make the processing of EEG a difficult task especially in real time environment where there is no control over the environment or the subject.

2.3 Emotion and Rhythmic Activity

There has been number of approaches to infer emotions from EEG rhythmic activity. Most emotions are found in the alpha band with different peak frequencies where the right hemisphere shows negative emotions such as fear, disgust and stress whereas the left hemisphere shows positive emotions such as happiness. Shemyakina et al. [24] show that significant differences in the local EEG power and spatial synchronization can be observed with different emotions. Musha et al. [17] showed that cerebral blood Flow (CBF) increases during sadness and decreases during happiness. The region that shows the difference between sadness and happiness is the frontal pole with left CBF being higher during sadness and lower during happiness.

Coan et al. [25] also showed that positive emotions are associated with relatively greater left frontal brain activity whereas negative emotions are associated with relatively greater right frontal brain activity. They also showed that the decrease in the activation in other regions of the brain such as the central, temporal and mid-frontal was less than the case in the frontal region.

Kostyunina et al. [1] showed that emotions such as joy, aggression and intention results in an increase in the alpha power whereas, emotions such as sorrow and anxiety results in a decrease in the alpha power. As for the valence and the arousal of emotions, Musha el al. [17] showed that valence of emotion is associated with asymmetries in the frontal lobe whereas, arousal is associated with generalized activation of both the right and the left frontal lobes.

Sammler et al. [26] showed that emotions elicited from musical stimulus resulted in an increase of frontal midline theta power. They suggest that the new findings of the effect of theta power on analyzing emotions in EEG is closely related to the interaction with attentional functions.

To sum up, alpha band is the most distinctive range of frequencies by which we can make use of to infer emotions from EEG signals and there might be some theta band effect. Also, EEG signals acquired from the right hemisphere can be a good predictive of negative emotions such as sadness, anger and fear whereas, EEG signals acquired from the right hemisphere can be a good indicative if positive emotions such as joy.

Chapter 3

Related Works

Detecting users' cognitive states and emotions are very useful in many different fields. One of these areas is usability engineering. They can provide information about the efficacy of the system interface and can provide information for system adaptation for better usability. Cognitive states, emotions and working memory load are also, important to show how hard the user is working to use an interface. This can be an important indicator of potential user's errors and a predictive way to know how well a user gets acquainted with the system. Another important field which cognitive state and emotion detection have a great effect on is monitoring the alertness state of the subject. This can help in monitoring people while working on safety critical systems such as air traffic control and nuclear power plants.

3.1 General Approach for Emotion/Cognitive State Detection

The general approach for any system that rely on brain signals is a layered approach as shown in Fig. 5.1. There are three main stages that the signals have to pass through in order to reach a final decision which are signal preprocessing, feature extraction and classification.

Figure 3.1: Multistage approach for emotion detection using EEG.

3.1.1 Signal Preprocessing

Signal preprocessing is the stage during which the signal is passed through a number of filters for artifact removal and for getting the signal ready for the next stages.

a. Artifact Removal

There are number of approaches followed for artifact removal. The easiest approach is to manually reject highly contaminated EEG signals and do not pass them through the other stages. However, the problem is that EEG studies do not have much data recorded so rejecting part of the data will make researchers loose number of trials. The other problem of this approach is that it means that only clean EEG data will be processed which make it difficult to apply the same approach to real applications because EEG will usually be contaminated with lots of artifacts as there will be no control on the environment of recording.

Another approach is to use artifact subtraction. This is done by using sensors that will record eye movements (EOG), facial muscles (EMG) and subtract these signals from EEG signals. The problem with this approach is that it requires more electrodes which usually placed on the face which will hinder the possibility of using them in real applications.

A third approach is to use low pass and high pass filters. Artifacts such as heart beats, eye movements and eye blinks are found in low frequency less than 3 Hz. Subsequently, a high pass filter can remove such artifacts. Also, line noise which are in the range of 50-60 Hz can be removed using a low pass filter. Although this is a very good technique for artifact removal, some EEG information from 0-3 Hz and from 50-60 Hz is lost.

Another more sophisticated technique is to use blind source separation (BSS). A well known method of BSS is Independent Component Analysis (ICA). ICA decomposes the signal into independent components. For instance, if we passed contaminated EEG data, we will get the EEG signal component and the artifacts signal component. One problem of using ICA is that it gives the two components of the signal without specifying which component is the EEG and which component is the artifact. This requires either using a manual technique to specify the EEG signal or to use a heuristic based approach to automatically select the EEG component as described in [27] . Another problem of using ICA is the time complexity. These two problems make it difficult to be applied in real time applications.

b. Common Reference

A widely used method of referencing is the common reference technique. This method used one common reference for all electrodes. The activity of the reference site is subtracted from all the activities of all the other electrodes. Researchers usually select electrodes placed on the right mastoid bone as a common reference.

c. Average Reference

Another method is the average reference. The average reference subtracts the average of the activity at all electrodes from the measurements. This method is based on the principle that the activity at the whole head at every moment sums up to zero. Therefore, the average of all activity represents an estimate of the activity at the reference site.

3.1.2 Feature Extraction

After removing the artifacts, signals pass through the feature extraction stage. Feature extraction is the process of selecting features that are representative to the specific cognitive or emotion state and selective from other extracted features so that we will not suffer from redundant features.

a. EEG Frequency Power Band

As previously explained, the brain signals have rhythmic activity and each rhythm can be captured from a specific region of the brain. Also, different set of information can be inferred from different rhythmic activities. One of the most commonly used methods is to convert the signal into the frequency domain using Fast Fourier Transform (FFT) or Power Spectral Density (PSD). After that features are extracted from the different frequency bands described in the previous chapter.

b. Spatial Domain Features

Other methods are used to extract features from the signal in the time domain. One of these approaches is using Hjorth parameters [28]. Hjorth described three parameters that can be extracted from EEG parameters which are activity, mobility and complexity.

- Activity, measures the mean power of the signal and it is measured as the standard deviation.
- Mobility, represents the mean frequency in the signal. It is computed as the ratio between the standard deviation of the slope and standard deviation of the amplitude.
- Complexity, is expresses as the number of standard slopes actually seen in the signa during the average time required for one amplitude.

c. Heuristic Features

Information other than EEG power band is generated as features. This includes the peak frequency in certain band as used by [1] or the number of electrodes whose power is greater than zero. Another feature is the number of positive features and the number of features above certain threshold.

3.1.3 Feature Reduction

Large number of features are generated during the feature selection stage that could exceed 100,000 features. This requires extracting relevant and distinctive features for the classification task.

There are several methods used for reducing the number of features. One of the most commonly used technique is principal component analysis (PCA). PCA is composed of a set of mathematical procedures that converts a set of correlated variables into a smaller set of uncorrelated variables. PCA starts with `k` training samples where each sample is represented by a vector

$$X = (x_1, x_2, ...x_m)$$

All training data are organized in a matrix X with each row as a vector X_i representing sample (i). The sum of each attribute (j) over the (k) samples is given by:

$$S_j = \sum_{i=1}^{k} X_{ij} \tag{3.1}$$

The mean $M - j$ for a given attribute (j) over the (k) samples is given by:

$$M_j = \bar{X} = \frac{1}{k} \sum_{i=1}^{k} X_{ij} \tag{3.2}$$

The vector of means will be

$$M = (M_1, M_2, ...M_m)$$

The standard deviation is then computed. The standard deviation (S.D.) is a measure of the spread of the data around the mean. The S.D. of each attribute over the (k) samples is given by:

$$\sigma_j = \sqrt{\frac{1}{k} \sum_{i=1}^{k} (X_{ij} - \bar{X}_j)^2} \tag{3.3}$$

The vector of S.D. for the m attributes is:

$$\sigma = (\sigma_1, \sigma_2, ...\sigma_m)$$

The covariance matrix is then computed. The covariance is a measure of the variability of two variables with respect to each other. So the correlation between every two variables is computed. If x and y are such two variables, then the covariance is defined as:

$$cov(x, y) = \frac{1}{k - 1} \sum_{i=1}^{k} (X_i - \bar{X})(Y_i - \bar{Y}) \tag{3.4}$$

Finally, the eigenvalues and eigenvectors are computed out of the covariance matrix. Let C, covariance matrix, be an (m x m) data matrix and V an (m x n) transformation

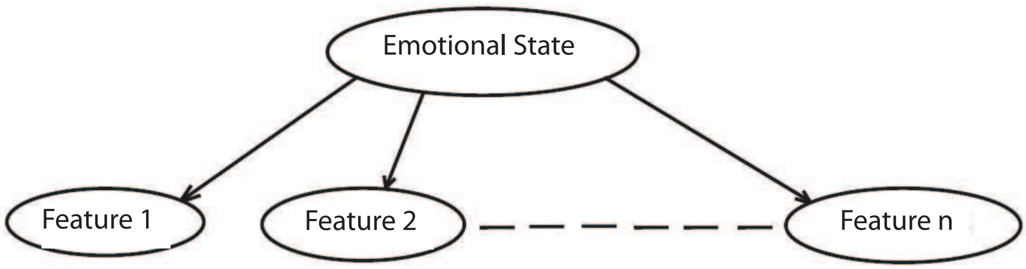

Figure 3.2: Bayesian Network DAG example. The emotional state node represents the hidden state whereas feature 1, feature 2,... feature n nodes represent the observed nodes. The edges represent the conditional dependencies between each feature and the emotional state.

matrix. The eigenvalue problem of C is to find the solutions of the system:

$$C.V = \lambda.V$$

The scalar λ is an eigenvalue of C, and V is the corresponding eigenvector.

When we project the original samples of attributes on that axis, the resulting values form a new variable. For the first eigenvector, the variance of this new variable is the maximum and its share in the variances of all the data is given by the first eigenvalue. The next maximum variance is given by the projection on the second eigenvector with the share given by the second eigenvalue, and so on. So, we can select the most relevant features by selecting those which have the highest eigenvalues.

3.1.4 Classification

After selecting distinctive uncorrelated features, the feature vector is passed to the classifier which infers which type of emotion such a vector represents. A classifier is sort of a function that is able to learn the relationship between feature vectors and their classes and given a new feature vector, it can infer to which class it belongs. There are number of different classifiers that are widely use.

a. Bayesian Networks

A Bayesian network [29], belief network, is a probabilistic graphical model that represents a set of random variables and their independencies using a directed acyclic graph (DAG) as shown in Fig 3.2. There are two types of nodes in the DAG, hidden nodes and observed nodes. The observed nodes are the extracted features, whereas the hidden node is the node that we want the inference engine to predict its probability of occurrence.

Edges between the node represent the conditional dependencies between the two given nodes connected to each other. Bayesian Networks are trained by given each node a prior probability which is the probability of occurrence of such random variables. After that a conditional probability table is constructed which gives the probability of each node given each of its parents. Hence, if the parents are m variables then the conditional probability table could be represented by a table of 2m entries, one entry for each of the 2m possible combinations of its parents being true or false.

Efficient algorithms exist that perform inference and learning in Bayesian networks. The probability of the hidden node is given by the following equation

$$P(E|F_1, F_2, F_3, ...F_N) = \frac{P(C)P(F_1, F_2, F_3, ...F_N|E)}{P(F_1, F_2, F_3, ...F_N)}$$

where E is the hidden node that could represent one of the emotions and F_1, F_2,...F_n represent the extracted features. $P(F_1, F_2, F_3, ...F_N|E)$ should be there because it is one of the values of the conditional probability table. If the features are independent so the value of $P(F_1, F_2, F_3, ...F_N)$ can be computed as

$$P(F_1, F_2, F_3, ...F_N) = \prod_{i=1}^{n} F_i$$

where F_i is given in the prior probability of each feature observed node.

b. Support Vector Machines

A Support Vector Machine (SVM) [30] is a supervised learning technique that is able to separate highly dimensional data. An SVM constructs a hyperplane that can have a linear or radial or polynomial shape between the data points of different classes as shown in Fig. 3.3. The hyperplane is constructed such that the separation between the points of the different classes is maximal.

SVMs are very powerful classifiers. Even though they only search for a separating hyperplane, They are able of finding very complex divisions between classes. The power of this method lies in the fact that the data are transformed into a high-dimensional space, using a kernel function. Using a proper transformation, it will be easier to separate the points in this higher dimensional space. If the separating hyperplane is constructed in

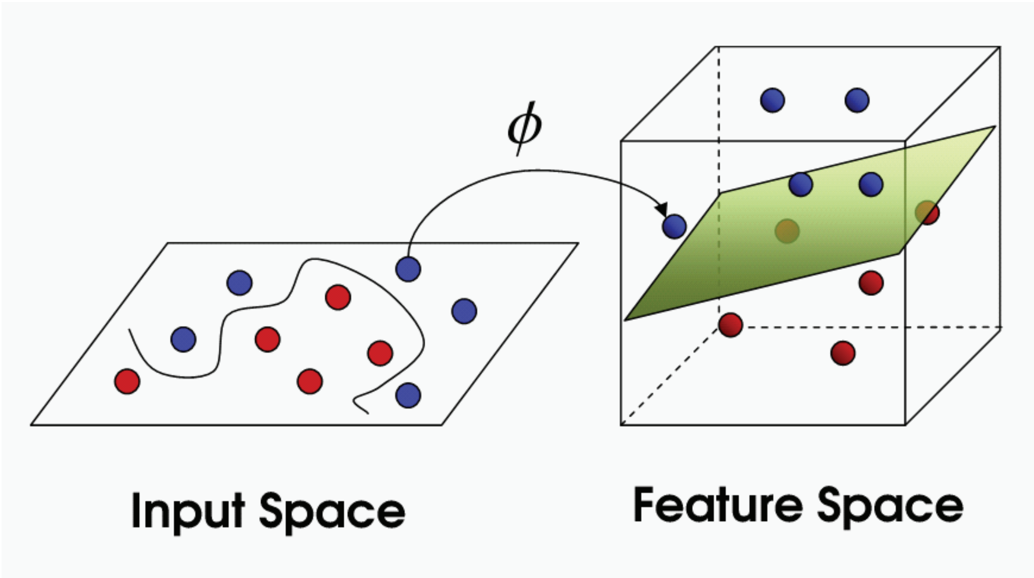

Figure 3.3: Support Vector Machines.

a N-dimensional space, where N is the number of training vectors, the data points can always be perfectly separated. However, the memory and computational demands increase dramatically with a larger training set.

3.1.5 Approaches of Eliciting Emotions

There are different psychological techniques for emotion elicitation. These techniques include using a stimulus to produce the required emotion or using an imagination technique or follow the facial feedback paradigm.

a. Presentation of Emotional Stimulus

Most of the approaches used in the literature use auditory or visual stimulus to entice emotions ad in [14] [15] [1]. In these research, an image from the International Affective Picture System (IAPS) [31] is shown to the participant for a number of seconds which is enough to entice this emotion. These images are usually coded on the valence-arousal scale.

Using images as a stimulus can be considered sort of event related potential on which an event takes a place and as a result, certain brain signals are produced. An example of joyful image from the IAPS database is shown in Fig. 3.4. This is the approach that is used in almost all the computer science research we are aware of.

Figure 3.4: An example of a joyful image from the IAPS database.

Other researchers use music or film excerpts as a stimulus. This technique is widely used and very successful as the self reports following the stimulus are relevant to the intended emotion.

b. Imagination Technique

The other approach is to ask the participant to remember or relive a situation where s/he felt certain emotional state. For instance, a participant may think of an accident that s/he saw which resulted in a negative emotional state.

Another imagination technique is using guided imagination. In guided imagination, the participants usually listen to a story or a scene that is often acted by actors. The participants might also, listen to a story on which the teller of the story inform the participants of what to feel or think.

This technique is widely used by psychologist but only used by Kostyunina et al [1] in computer science research. The major limitation of such technique is that it is not an actual emotion, it is considered to be a relived emotional state.

c. Facial Feedback Paradigm

The idea behind the technique that is based on the facial feedback paradigm is to ask participants to perform certain facial expressions that will result in the required emotion at the end. This approach may be superior to the other forms of induction as Ekman et al. [20] found that emotions generated with a directed facial action task results in a finer distinction between emotions. However, this approach contaminates brain signals with facial muscle artifacts and that's why this approach is not conceived by computer scientists. We decided to explore this approach because it was not used in the literature and because it helps making our system close to actual real time emotion detection systems since there will be lots of facial muscle and other artifacts that will contaminate our EEG data.

3.2 Cognitive State Detection using EEG

Cognitive state detection has been around for quite some time. There are some interesting conclusions that were made by neuroscientists in this area. Kilmesch et al [32] found that the decrease in the theta rhythm and the increase in the beta rhythm indicate the presence of higher memory load. The problem is that these indicators are only valid when averaged over large amount of time and over data captured from different number of users. This can be considered a problem especially for real time applications. They also, use 32 electrodes for experimentation which hinders integrating their approaches in real time system.

Grimes et al [33] tried to devise a technique for reliable measurement of working memory load to be used in real time adaptable systems. They managed to reduce the number of electrodes to only 8 electrodes, have their system trained on smaller datasets and experiment with smaller window sizes so that their approach can be used in real time systems. They managed to reach an accuracy of 99% in classifying between two levels of working memory load and 88% in classifying between four levels of working memory loads which differ in the mental effort the user has to exert in order to use the application. In order to produce different memory workloads, Grimes et al [33] used the N-back task technique. In their experiments, a sequence of images or letters will be viewed to the participant. The participant will be given a letter or an image and asked whether this letter or image appeared in the sequence N letters before. The variation in the value of N will result in higher memory load.

For the signal processing, the authors down sampled the captured signals to only 256 Hz using a low pass filter. They divided the signal into overlapping widows and then converted it into the frequency domain using power spectral density estimation (PSD). As for feature generation, they divided the signal into three power bands. They collected the values of signal power ranging from 4 Hz to 13 Hz in 1 Hz intervals. They also, collected the values of signal power ranging from 14 Hz to 31 Hz in 2 Hz intervals. Finally, they collected the values of signal power ranging from 32 Hz to 50 Hz in 4 Hz interval. The reason why they made such choices is to have higher resolution estimates and more distinct features in these smaller power bands. Feature selection and dimensionality reduction is done by selecting the most predictive and robust features using relative information gain criteria. This is done by descrediting each feature into 15 equally spaced bins and calculating mutual information based on Nave Bayes density model.

As for the classification, Grimes et al [33] propose using 24-fold cross validation. They made sure that the selected training sets are drawn from blocks that are different from those used for testing. The reason why they made such choice is to make sure that the training data are not found close to the testing data which will overestimate their accuracy of the system and will not be suitable for a real time HCI system. Grimes et al [33] experimented with different number of EEG electrodes that range from only 1 electrode to 32 electrodes. They showed that 8 electrodes provide a good tradeoff between accuracy and speed. They also, experimented with different window sizes that range from 2 seconds to 120 seconds and showed the tradeoff between the accuracy and the choice of the window size which is considered to be a major factor on applying the approach in real time systems.

Another approach for mental task classification was proposed by Lee and Tan [34]. The main purpose of their approach is to prove that they can detect mental states with a low cost EEG data acquisition and amplifiers and with only 2 electrodes. The authors were able to classify between three main mental tasks which are rest, mathematical calculation and geometric rotation. The participants are asked to stay still and to perform all the actions while their eyes are closed. These instructions were gives to the subjects in order to minimize the motion and eye movement artifact. The participants are given the instructions aurally and they are asked to perform the action within a given time period.

For the signal processing, Lee and Tan [34] suggests transforming the signal into the frequency domain. They do that by slicing the EEG signal into small overlapping windows and then take the Fourier Transform of the resulted signal. For each window, the authors compute the signal power in each of the six frequency bands for each electrode, the phase coherence in each band across the electrodes and each band power difference between the two electrodes. In addition to these features, they compute the mean spectral power, peak frequency, peak frequency magnitude, mean phase angle, mean sample value, zero crossing rate, number of samples above zero and the mean spectral power difference. After that they compute the product and division of each pair of features. The reason why they do that is the fact that non linear manipulation of features is a common machine learning technique used to compensate for potential lack of expressiveness in the statistical model used for classification. After feature extraction, the authors apply Weka's VfsSubsetEval operator for dimensionality reduction. This operator reduces the number of features to only 51 features. They then applied a more computationally expensive feature selection process that builds a classifier with an empty set. The algorithm stars to add or remove features based on their effect on the overall accuracy. Finally, they used a Bayesian network classifier to identify the three different tasks. The used 10 fold cross validation as in [33] and reached an average accuracy of 84%. The major drawback of this approach is that it is not suitable for real time application where there will be lots of motion and eye blinks.

Another type of cognitive tasks is alertness. An approach for measuring users' alertness is proposed by Jung et al [35]. In order to collect EEG data, the participants are seated in front of a computer. The participants receive ten different visual and auditory stimuli per minute. For each stimulus, the user has to press a button to show whether the stimulus was visual or auditory. The time required by the user to press the button in response to the stimulus defines how alert the user is.

After recording the signal, Jung et al [35] suggest using a heuristic based approach for artifact removal. They suggest removing parts of the signals that are below or above 50 uV because they are produced due to eye blinks and muscle movement. After that a median filtering using a moving a 5-sec window was used to further minimize the presence of artifacts. After artifact removal, the signal is converted to a logarithmic scale. Due to the variability of EEG signals from one subject to another, Jung et al [35] suggests using artificial neural networks due to its flexibility and strong discriminative power. Principal Component Analysis (PCA) was applied to the full EEG log spectral data on the subspace formed by the eigenvectors corresponding to the largest eigenvalues. The authors found that using only 4 principal components will result in accuracy of 89%.

The area of cognitive detection using EEG has captured the attention of researchers working in the US market. One of the US application patents that describe a technique of task classification and recognizing activity is proposed by Microsoft Corporation [36]. The main goal of this patent is to make use of users' cognitive state to provide a better user interface for better usability. Tan and Lee [36] propose a method for classifying brain states using EEG signals. The captured data will be divided into a number of overlapping windows. Each window is transformed to the frequency domain and then features are generated from the data in the EEG power spectrum. More features will be generated using the EEG base features and then they propose applying a feature selection algorithm for dimensionality reduction. The authors are suggesting similar techniques to that described in [34]. There are number of mental states that are of great importance such as cognitive workload, task engagement, communication mediation, interpreting and predicting system response, surprise, satisfaction, and frustration. The goal of this patent is to distinguish between at least two of these cognitive states and to determine the transition between the different mental states.

3.3 Emotion Detection using EEG

One of the earliest attempts to prove that EEG signals can be used for emotion detection is proposed by Chanel et al [14]. Chanel et al [14] were trying to distinguish among excitement, neutral and calm signals. They compared the results of three emotion detection classifiers. The first one was trained on EEG signals, the second classifier was trained on peripheral signals such as body temperature, blood pressure and heart beats. The third classifier was trained on both EEG and peripheral signals. In order to use EEG signals, they used a bandpass filter to remove both technical and physiological artifacts. In order to stimulate the emotion of interest, the user is seated in front of a computer and is viewed an image to inform him/her which type of emotion s/he has to think of. They then captured the signals from 64 different electrodes that cover the whole scalp. The reason why they used 64 electrodes is to capture signals in all the rhythmic activity of the brain neurons. As for feature extraction, they simply transformed the signal into the frequency domain and use the power spectral as the EEG features. Finally, they used a Naive Bayes Classifier which resulted in an average accuracy of 54% compared to only 50% for a classifier trained on physiological signals. The accuracy of combining both types of signals resulted in a boost of accuracy that reached up to 72%.

The problem with the research done by Chanel et al [14] is the idea of using 64 electrodes which results in large processing time which hinders the fact of using this system in real time. They also, used simple feature extraction and classification algorithms which resulted in the low 54% accuracy. Ansari et al [15] improved the work done by Chanel et al [14]. They proposed using Synchronization Likelihood (SL) method as a multi-electrode measurement which allowed them along with anatomical knowledge to reduce the number of electrodes from 64 to only 5 with a slight decrease in accuracy and huge improvement in performance. The goal is to distinguish between three emotions which are exciting-positive, exciting-negative and calm. For signal acquisition, they acquired the signal from (AFz, F4, F3, CP5, CP6). For feature extraction, they used sophisticated techniques such as Hjorth Parameters and Fractal Dimensions and they then applied Linear Discriminant Analysis (LDA) as their classification technique. The results showed an average accuracy of 60% in case of using 5 electrodes compared to 65% in case of using 32 electrodes.

Another approach was adopted by Kostyunina et al [1]. They used 10 different electrodes located at F3, F4, C3, C4, T3, T4, P3, P4, O1, O2 in order to differentiate between four emotions which are joy, anger, fear and sorrow. Kostyunina et al [1] applied a low pass filter to reject all frequencies higher than 30 Hz. They applied FFT and focused on getting the features from the range of [0-30] with resolution of 0.2 Hz. The interesting thing about this research is that the authors used event related desynchronization in which the subjects are asked to imagine a situation that will result in changing their emotion to one of the four emotions of interest. Kostyunina et al [1] reached the conclusion that joy and anger emotions result in an increase in the peak frequencies of the alpha band whereas the case of fear and sorrow emotions result in a decrease in the peak frequencies of the alpha band.

A different technique was taken by Musha et al [17]. They used 10 electrodes (FP1, FP2, F3, F4, T3, T4, P3, P4, O1, and 02) in order to detect of four emotions which are anger, sadness, joy and relaxation. They rejected frequencies lower than 5 Hz because they are affected by artifacts and frequencies above 20 Hz because they claim that the contributions of these frequencies to detect emotions is small. They then collected their features from the theta, alpha and beta ranges. They performed cross correlation on each electrode pairs. The output of this cross correlation is a set of 135 variables that is linearly transformed to a vector of 1x4 using a transition matrix. Each value indicates the magnitude of the presence of one of the four emotions. This means that any testing sample will be a linear combination of the four emotions. After that they apply certain threshold to infer the emotion of interest. Creating the transition matrix is done by collecting data from 9 different subjects who were trained to make 4 emotions. The training data are divided into two sets and the transition matrix was generated on one set and tested on another.

Another research was done by Murugappan et al [37]. The purpose of this research was to investigate whether using an audio-visual stimulus yields better induction of emotional states or using visual stimulus only. Murugappan et al [37] investigated the possibility of using visual and audio visual stimulus for detecting the human emotion by measuring electroencephalogram (EEG). They designed Visual and audiovisual stimulus based protocols to acquire the EEG signals over five healthy subjects using 63 bio sensors that were placed all over the surface of the scalp. They analyzed the EEG signals using discrete wavelet transform and used neural networks for classification. EEG signals were decomposed into five frequency sub-bands using 'db4' wavelet function and two statistical features were extracted from the alpha band. These statistical features were used as input to the neural network for classifying five emotions (disgust, happy, surprise, sad and anger). In the experiments of recognizing human emotions from visual and audiovisual stimulus, they reached average recognition rate of 56.66% and 66.67% for the visual and audiovisual stimulus respectively. They reached a conclusion that the audiovisual stimulus based emotion recognition gives better classification accuracy over visual stimulus.

Another technique for feature extraction was proposed by Murugappan et al [38]. They designed a competent acquisition protocol for acquiring the EEG signals. The brain signals were produced as a result of audio-visual stimulus. The EEG data has been collected from 6 healthy subjects with in an age group of 21-27 using 63 bio sensors. Three emotions have been identified with higher agreement. After preprocessing the signals, discrete wavelet transform is employed to extract the EEG parameters. Murugappan et al [38] wanted to prove that wavelet transforms can result in distinctive features. The feature vectors derived from the wavelet transform on 63 biosensors form an input matrix for emotion classification. They then used Fuzzy C-Means (FCM) and Fuzzy k-Means (FKM) clustering methods for classifying the emotions. They also analyzed the performance of FCM and FKM on reduced number of 24 biosensors model. Finally, they compared the performance of clustering the discrete emotions using FCM and FKM on both 64 biosensors and 24 biosensors. Their results showed the possibility of using wavelet transform based feature extraction for assessing the human emotions from EEG signal.

Another EEG emotion detection system is proposed by Li et al [39]. Li et al [39] proposed an emotion recognition system based on time domain analysis of the bio-signals for emotion features extraction. Li et al [39] were trying to make use of the spatial domain features to differentiae between three different types of emotions (happy, relax and sad).

Three selected videos from youtube were used as stimulus for each emotion. A survey was conducted among 30 human subjects who did not participate in the experiments to evaluate the integrity of the videos to invoke the respective emotions. In order to gather the EEG data, they showed the videos to five Chinese participants, 3 males and 2 females. For feature extraction, they extracted six spatial domain features. They did not apply any signal preprocessing tasks for noise removal. For classification, they used the relevance vector machines (RVM) which share lots of characteristics with SVM.

A new emotion elicitation technique is proposed by Mikhail et al [40]. Mikhail et al [40] proposed using an approach builds on the facial feedback paradigm which shows that facial expressions are robust elicitors of emotional experiences. 36 subjects (10 males and 26 females) were asked to make certain facial expressions that correspond to four different emotions: anger, fear, joy and sadness. For feature extraction, they focused on extracting features from the alpha band only and making use of the changes between the voltages of the right and left hemisphere relative to positive and negative emotions. They succeeded in reducing the number of features from 145000 features to only 3654 features. Finally, they were able to reach an average accuracy of 51% for joy emotion, 53% for anger, 58% for fear and 61% for sadness.

Other research implies a multimodal technique for emotion detection. One of these studies was done by Savran et al [16]. They propose using EEG, functional near-infrared imaging (fNIRS) and video processing. fNIRS represents a low-cost, user-friendly, practical device for monitoring the cognitive and emotional states of the brain. fNIRS detects the light that travels through the cortex tissues and is used to monitor the hemodynamic changes during cognitive and/or emotional activity as shown in Fig. 3.5. Savran et al [16] combined EEG with fNIRS along with some physiological signals in one system and fNIRS with video processing in another system. They decided not to try video processing with EEG because facial expressions result in much in noise in the EEG signals. Also, when they recorded both EEG and fNIRS, they excluded the signals captured from the frontal lobe because of the noise produced by the fNIRS recordings. For experimentation, they showed the participant images that will induce the emotion of interest and then recorded fNIRS, EEG and video after showing these images. The most difficult part of this research is making an accurate synchronization mechanism for making the different recordings at the same time especially because every device was made to be used alone so they managed to run each system on a different computer and send a trigger to all computers at the time of showing the stimulus. The fusion among the different modalities is done on the decision level and not on the feature level.

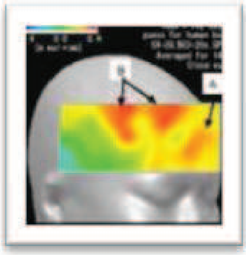

Figure 3.5: The figure shows how FNIRS detects the light that travel through the cortex.

Figure 3.6: Emotiv headset with 16 electrodes to cover the different parts of the brain.

There are a number of products that are currently available in the US market and are based on detecting emotions using EEG. One of these products is Emotiv Systems headset. The researchers at Emotiv developed a methodology for detecting and classifying mental states [41]. They developed a headset with up to 16 electrodes shown in Fig. 3.6. This headset covers the four main regions of the brain. After capturing the signal, a signal preparation is performed. This includes noise filtering and artifact removal using techniques such as Independent Component Analysis (ICA). After that they start buffering the captured EEG signals and then they transform the buffered data to the frequency domain and extract features based on the different power bands. Due to the large number of extracted features, they apply some techniques for feature refinement and then they apply a method for detecting and classifying mental states which include emotions such as instantaneous excitement, long term excitement and boredom/engagement. The authors claim that different mental states and emotions result in the change and the increase of the signal power of one or more than one bio-signal representations [41].

In order to make sure that Emotiv system works for new users, Emotiv system allows the new user to train the system on his/her signals so that the classification accuracy increases. This is done by a method of calibrating the signature for use in the method of detecting and classifying the mental state [41].

3.4 The Problem of Emotion Detection using EEG

As we have seen from the related works, the area of emotion detection using EEG is relatively new. There is much work that can be done to enhance the current state of the art. The available systems have two main drawbacks. The main disadvantage of the previously mentioned research is the use of constrained environment to capture emotion related EEG data in which the participants are asked to reduce their facial expressions and head motions. Moreover, highly contaminated EEG data with noise are rejected and removed from the analysis. This affects the possibility of integrating such approaches into real applications where there are no constraints on the participants.

Another disadvantage is that some of the previously mentioned systems [14] [16] [1] [17] are using large number of electrodes to acquire EEG signals or EEG and physiological signals. The number of such electrodes range from 10 to 32 electrodes which affects the portability of such systems and hinders the possibility of making these systems run in real time. Moreover, as the number of electrodes increase, the processing time increases as each electrode will pass through all the stages of the different approaches. Another problem with large number of electrodes is that it will require sophisticated headset which will again affect the portability of such systems.

In order to provide better solutions to the drawbacks of the prior work, we focused our research on applying different experiments that were not applied before. First, since the main problem with prior art is the use of constrained environment which makes such approaches difficult to be applied in real life situation, we thought of experimenting with a totally new elicitation technique that depends on using voluntary facial expression as a means for enticing emotions. Hence, instead of using a database that is free from artifacts such as head motions, eye blinks and facial expressions, we used a database that is highly contaminated with noise produced from facial expression. This can make our experiments be applied on a dataset that is close to real life situations where there will be no control over the user.

Also, instead of applying PCA or any algorithm for dimensionality reduction, we thought of experimenting with feature sets that were reduced based on some ideas that we gathered from neuroscience findings. So we focused on inferring some equations for reducing the number of features that were fed into the classifier. We generated two different feature sets and applied different classifiers to such feature sets.

Finally, in order to solve the other problem of the prior work which is the use of large number of electrodes, we experimented with different number of electrodes that range from 4 up to 25 electrodes. We used two different techniques for selecting the electrodes to be eliminated. Our main goal was to reach a reasonable accuracy with the fewest possible number of electrodes so that our approach can be easily integrated in real life situations since the fewer the number of electrodes the more convenient the system will be for the user.

Chapter 4

Methodology

One of the problems of the current emotion detection systems using EEG is the use of constrained environment to capture emotion related EEG data in which the participants are asked to reduce their facial expressions and head motions. Moreover, highly contaminated EEG data with noise are rejected and removed from the analysis. This affects the possibility of integrating such approaches into real applications where there are no constraints on the participants.

Another disadvantage is that some of the previously mentioned systems [14] [16] [1] [17] are using large number of electrodes to acquire EEG signals or EEG and physiological signals. The number of such electrodes range from 10 to 32 electrodes which affects the portability of such systems and hinders the possibility of making these systems run in real time. Moreover, as the number of electrodes increase, the processing time increases as each electrode will pass through all the stages of the different approaches. Another problem with large number of electrodes is that it will require sophisticated headset which will again affect the portability of such systems.

Given the problems of the previously mentioned state of art, the goal of this research is to extend existing research in three principal ways.

1. Instead of using a visual or an auditory stimulus for emotion elicitation, we decided to use voluntary facial expression based on the facial feedback paradigm which shows that facial expressions are robust elicitors of emotional experience, as a means for eliciting emotions. We asked professor John J.B. Allen from the psychology department in the university of Arizona to share his database of EEG signals with us. The reason we used this database is because the signals are recorded by highly trained people who have been

working in the field for more than 10 years. Also, studying emotions is mainly done by psychologists, so they are very experienced in recording EEG signals relate to different emotions. Finally, they used sophisticated data acquisition devices which is not available to us. Although this contaminates EEG with noise, it helps to test our approach on unconstrained environment where the users will not be given any special instructions about reducing head motions or facial expressions.

2. We used a new technique for selecting features that are relevant to the emotion detection task that is based on two main neuroscience findings. The first neuroscience finding is the fact that emotions are most obvious in the alpha band which ranges from 7 to 13 Hz [1]. The second neuroscience finding is that positive emotions result in relatively greater left brain activity and negative emotions result in greater right brain activity. So we decided to focus our experiments on the alpha band and making use of scalp asymmetries in case of positive and negative emotions. We experimented with different sets of features and showed how the classification accuracy changes with each set of features.

3. Since one of the drawbacks of the previous work is the use of large number of electrodes which hinders the portability of such systems, we applied our approach on different number of electrodes that range from 4 to 25 electrodes. This can make our system more portable and can be used in real applications. Our goal was to reach a reasonable accuracy with the fewest number of electrodes especially because UCSD has devised a new cap with only seven wireless electrodes that can be used in real systems [42]. So our goal was to reach a reasonable accuracy with only seven electrodes.

4.1 Research Method

4.1.1 EEG database

In this research, we used the database of EEG signals collected in the university of Arizona by Coan et al. [25].

4.1.2 Participants

This database contains EEG data recorded from thirty-six participants (10 men and 26 women) [25]. All participants were right handed. The age of the participants ranged from 17 to 24 years, with a mean age of 19.1. The ethnic composition of the sample was 2.7%

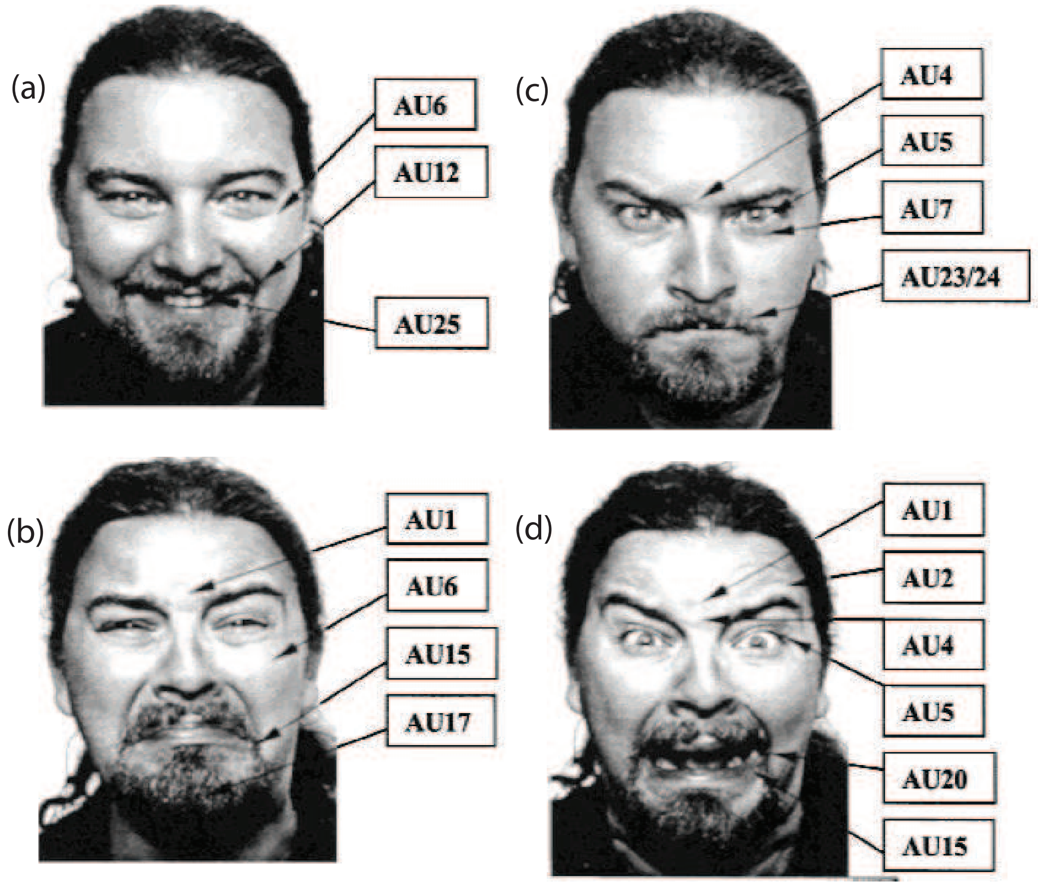

Figure 4.1: Muscle movements in the full face conditions: (a) joy, activating AUs 6 (cheek raiser), 12 (lip corner puller), and 25 (lips part); (b) sadness, activating AUs 1 (inner brow raiser), 6 (cheek raiser), 15 (lip corner depressor), and 17 (chin raiser); (c) anger, activating AUs 4 (brow lowerer), 5 (upper lid raiser), 7 (lid tightener), 23 (lip tightener), and0or 24 (lip pressor); (d) fear, activating AUs 1 (inner brow raiser), 2 (outer brow raiser), 4 (brow lowerer), 5 (upper lid raiser), 15 (lip corner depressor), and 20 (lip stretch) [25].

African American, 2.7% Asian, 18.9% Hispanic, and 75.7% Caucasian.

4.1.3 Procedure

According to Coan et al. [25], the experimenter informed participants that they were taking part in a methodological study designed to identify artifacts in the EEG signal introduced by muscles on the face and head. Participants were further told that accounting for these muscle movement effects would require them to make a variety of specific movements designed to produce certain types of muscle artifact. The presence of such muscle artifacts make the problem of emotion detection using EEG very difficult because the EEG signals will be contaminated with muscle artifacts which gets it close to real time applications where there will be no control over the facial muscles or other sources of noise.

Participants were led to believe that they were engaged in purposely generating error-muscle artifact. It was hoped that although participants might detect the associations between the directed facial action tasks and their respective target emotions, they would not think of the target emotions per se as being of interest to the investigators. After participants were prepared for psychophysiological recording with EEG and facial EMG electrodes , participants sat quietly for 8 min during which resting EEG was recorded during a counterbalanced sequence of minute-long eyes-open and eyes-closed segments.

For the facial movement task, participants were seated in a sound-attenuated room, separate from the experimenter. The experimenter communicated with participants via microphone, and participants faces were closely monitored at all times via video monitor. Participant facial expressions were recorded onto videotape, as were subsequent verbal self-reports of experience. The experimenter gave explicit instructions to participants concerning how to make each facial movement, observing participants on the video monitor to ensure that each movement was performed correctly.

Participants were asked to perform relatively simple movements first, moving on to more difficult ones. For example, the first movement participants were asked to perform is one that is part of the expression of anger. This movement engages the corrugator muscle in the eyebrow and forehead drawing the eyebrows down and together. Subjects were asked to make the movement in the following manner: "move your eyebrows down and together." This was followed by two other partial faces, making three partial faces in all. No counterbalancing procedure was used for the control faces, as they were all considered to be a single condition.

One of the approaches that describes facial movements and their relation with different emotions is the Facial Action Coding System (FACS) [43], a catalogue of 44 unique action units (AUs) that correspond to each independent motion of the face. It also includes several categories of head and eye movements. FACS enables the measurement and scoring of facial activity in an objective, reliable and quantitative way. Expressions included joy (AUs 6 + 12 + 25), anger (AUs 4 + 5 + 7 + 23/24), fear (AUs 1 + 2 + 4 + 5 + 15 + 20), sadness (AUs 1 + 6 + 15 + 17) and disgust (AUs 9 + 15 + 26) can be shown in Fig 4.1. These kinds of action units are used to entice such emotions.

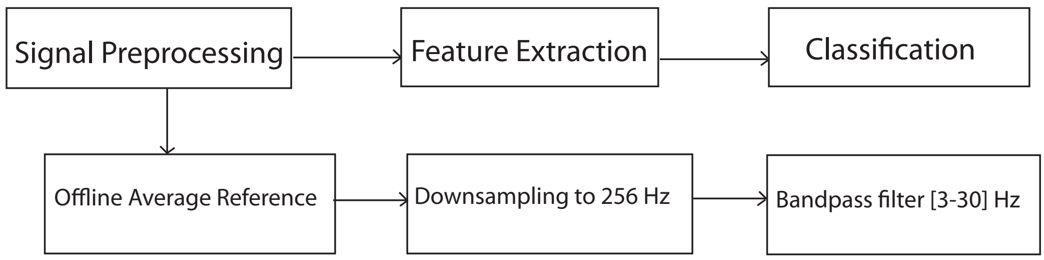

Figure 4.2: Three stages for analyzing the signal, preprocessing, feature extraction and classification. In the signal preprocessing stage, three filters are used.

4.1.4 Signal Preprocessing

Fig. 4.2 shows the three stages that EEG data are passed through during the signal preprocessing stage which are offline average reference, downsampling and bandpass filter.

4.1.4.1 Offline Average Reference and Downsampling

Our EEG data is referenced online to Cz.

- offline average reference, According to the recommendation of Reid et al [44] who pointed out that this online referencing scheme did not correlate particularly well, an offline average reference is performed for the data by subtracting from each site average activity of all scalp sites.
- downsampling, After that our data are downsampled from 1024 Hz to 256 Hz to reduce the amount of data.

4.1.4.2 Noise Reduction using Bandpass Filter

One of the main problems that affect the accuracy of processing EEG is the large contamination of the signals with artifacts. There are two main sources of noise that may contaminate the recorded EEG signal which are technical artifacts and physiological artifacts.

a. Technical Artifacts

The technical artifacts are usually related to the environment where the signals are captured. One source of technical noise is the electrodes itself. If the electrodes are not properly placed over the surface of the scalp or if the resistance between the electrode and the surface of the scalp exceeds 5 kohm, this will result in huge contamination of the EEG.

Another source of technical artifact is the line noise. This noise occurs due to A/C power supplies which may contaminate the signal with 50/60 Hz if the acquisition electrodes are not properly grounded.

b. Physiological Artifacts

Another sources of noise are the physiological artifacts. Physiological artifacts are related to the subject undergoing the EEG recording. Those physiological artifacts include eye blinking, eye movements, Electromyography (EMG), motion, pulse and sweat artifacts. The problem in eye blinking is that it produces a signal with a high amplitude that is usually much greater than the amplitude of the EEG signals of interest. Eye movements are similar to or even stronger than eye blinks. The EMG or muscle activation artifact can happen due to some muscle activity such as movement of the neck or some facial muscles. This can affect the data coming from some electrodes, depending on the location of the moving muscles. As for the motion artifact, it takes place if the subject is moving while EEG is being recorded. The data obtained can be corrupted due to the signals produced while the person is moving, or due to the possible movement of electrodes. Another involuntary types of artifacts are pulse and sweat artifacts. The heart is continuously beating causing the vessels to expand and contract; so if the electrodes are placed near blood vessels, the data coming from them will be affected by the heartbeat. Sweat artifacts can affect the impedance of the electrodes used in recording the brain activity. Subsequently, the data recorded can be noisy or corrupted. These different types of noise make the processing of EEG a difficult task especially in real time environment where there is no control over the environment or the subject.

Our dataset is largely contaminated with facial muscle and eye blink artifacts. Moreover, there are segments that are highly contaminated with artifacts and are marked for removal. Instead of rejecting such segments, we included them in our analysis so that our approach can be generalized to real time applications. Since most of the previously mentioned artifacts appear in low frequencies, we used a band pass finite impulse response filter that removed the frequencies below 3 Hz and above 30 Hz.

4.1.5 Feature Extraction

Feature extraction is the process of selecting relevant features from the EEG data for training and classification. Each feature should be distinctive from other features and representative of the class. We used three different techniques for selecting the features. First, our analysis started by taking the whole 30 seconds and divide them into 2-second window with a 1-second overlap. Each window is converted into the frequency domain using Fast Fourier Transform (FFT) as shown in Fig. 4.3.

The frequency descriptors of the power bands, theta, alpha and beta rhythms, were extracted. This resulted in a huge feature set of 145000 features that is computed as

# of features = (# windows x # electrodes x # features per window)

- # windows, taking the whole 30 second epoch and dividing it into a 2 second window with 1 second overlap, will result into 29 windows.
- # electrodes, we used the whole 25 electrodes that are placed over all the regions of the scalp.
- # features per window, we extracted 100 frequency descriptors that represent the power band of the delta, theta, alpha, beta and gamma rhythms. We also, extracted 100 phase angle features that represent the same bands. we also extracted 5 heuristic features such as mean power, mean phase angle, peak magnitude, the frequency with the highest magnitude and number of frequency descriptors that are more than zero.

This will result in 205 features per window which resulted in approximately 145000 features.

4.1.5.1 Feature Reduction using Domain Knowledge

We used two main techniques for reducing the number of extracted features which are using the alpha band only and making use of the scalp asymmetries that take place during positive and negative emotions.

a. Alpha Band

We made use of the study made by Kostyunina et al. [1] in order to reduce our feature set. Kostyunina et al. [1] showed that emotions such as joy, aggression and intention results in an increase in the alpha power whereas, emotions such as sorrow and anxiety results in a decrease in the alpha power. As a result of this conclusion, we focused our feature extraction on the alpha band only which ranges from 7Hz to 13 Hz for the 25 electrodes. This helped in decreasing the number of features from 145000 to 10150 features,

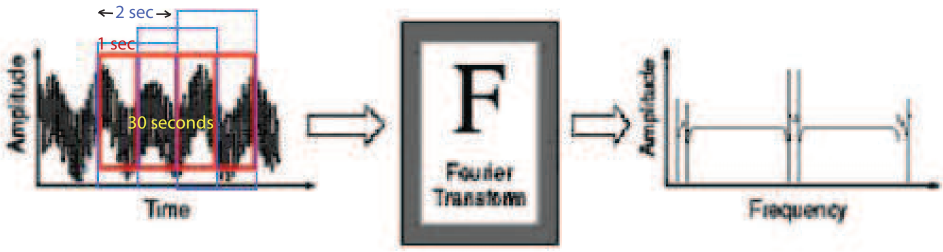

Figure 4.3: Applying FFT to overlapping windows.

14 (feature/window) x 29 (window/electrode) x 25 (electrodes) = 10150. The 14 features in each window include the 7 FFT frequency descriptors and 7 phase angles in the alpha band only.

b. EEG Scalp Asymmetries

Another important research that we made use of in order to reduce our feature set is the research done by Coan et al. [25]. Coan et al. [25] showed that positive emotions are associated with relatively greater left frontal brain activity whereas negative emotions are associated with relatively greater right frontal brain activity. They also showed that the decrease in the activation in other regions of the brain such as the central, temporal and mid-frontal was less than the case in the frontal region. This domain specific knowledge helped us in decreasing the number of features from 10150 to only 2233 features, 7 (feature/window) x 29 (window/electrode) x 22 (electrodes) / 2 (asymmetry) = 2233. The 7 features include the alpha descriptors only without the phase angle. The reason why we used 22 electrodes only because we need to include symmetric electrodes only. For instance, F7 and F8 are symmetric with resect to the center of the brain. So There are not symmetric electrodes for 3 out of the 25 electrodes.

4.1.6 Training and Classification

As for training and classification, we used K-fold cross validation in order to select the best training set for our classifier. For the classification, we decided to use support vector machines.

4.1.6.1 K-Fold Cross Validation

In K-fold cross-validation, the dataset is divided into two partitions, the training set and the testing set. The classifier is trained using the training set and then is tested against the testing set. The cross-validation process is then repeated K times (the folds), with each of the training and testing set are used exactly once.

The results from the different folds can then be averaged to produce an estimate of the classification accuracy. We selected the training and testing set randomly in which we held out 10 % of the samples to be used for testing and the rest of the samples were used for training.

4.1.6.2 Support Vector Machines (SVMs)

As mentioned earlier, Support Vector Machine (SVM) is a supervised learning technique. Given a training set of feature vectors, SVMs try to find a hyperplane such that the two classes are separable and given a new feature vector, SVMs try to predict to which class this new feature vector belongs to. So given the extracted features, the SVM classifier would predict which emotion these features represent.

We experimented with different kernels, linear, polynomial and radial. for the SVMs. We built four different binary classifiers, one for each emotion. For instance, we trained the joy classifier with feature vectors representing joy as one class and feature vectors representing all other emotions as the other class.

4.1.7 Tools

4.1.8 MATLAB

MATLAB is a numerical computing environment and fourth generation programming language. Developed by The MathWorks, MATLAB allows matrix manipulation, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs in other languages. The availability of large number of filters, feature extraction and classification toolbox is the main reason why we decided to use MATLAB as our development environment.

EEGLAB

EEGLAB [45] is an interactive MATLAB toolbox for processing continuous and event-related EEG, MEG and other electrophysiological data incorporating independent component analysis (ICA), time/frequency analysis, artifact rejection, event-related statistics, and several useful modes of visualization of the averaged and single-trial data.

EEGLAB provides an interactive graphic user interface (GUI) allowing users to flexibly and interactively process their high-density EEG. EEGLAB offers a wealth of methods for visualizing and modeling event-related brain dynamics, both at the level of individual EEGLAB 'datasets' and/or across a collection of datasets brought together in an EEGLAB 'study set.'

4.1.9 LIBSVM

LIBSVM [46] is a library for Support Vector Machines available in many programming languages including MATLAB. LIBSVM is an integrated software for classification, regression and distribution estimation (one-class SVM). It supports multi-class classification.

Chapter 5

Experimental Evaluation

5.1 Approach For Emotion Detection Using EEG

As shown in Fig. 5.1, we use a multilevel approach for analyzing EEG to infer the emotions of interest. First, the signal preprocessing stage was activated in which a number of filters were applied on the EEG signals for adjusting the signals, reducing the amount of recorded data and for noise removal. After that relevant features were extracted from the signals and finally we used support vector machines for classification.

5.1.1 Signal Preprocessing

Fig. 5.1 shows the three stages that EEG data is passed through during the signal preprocessing stage. Our EEG data are referenced online to Cz.

- offline average reference, According to the recommendation of Reid et al [44] who pointed out that this reference scheme did not correlate particularly well, an offline average reference is performed for the data by subtracting from each site average activity of all scalp sites.

- downsampling, After that our data are downsampled from 1024 Hz to 256 Hz to reduce the amount of data.

- bandpass filter, our dataset is largely contaminated with facial muscle and eye blink artifacts. Moreover, there are some segments that were inspected manually were found to be highly contaminated with artifacts and were marked for removal. Instead

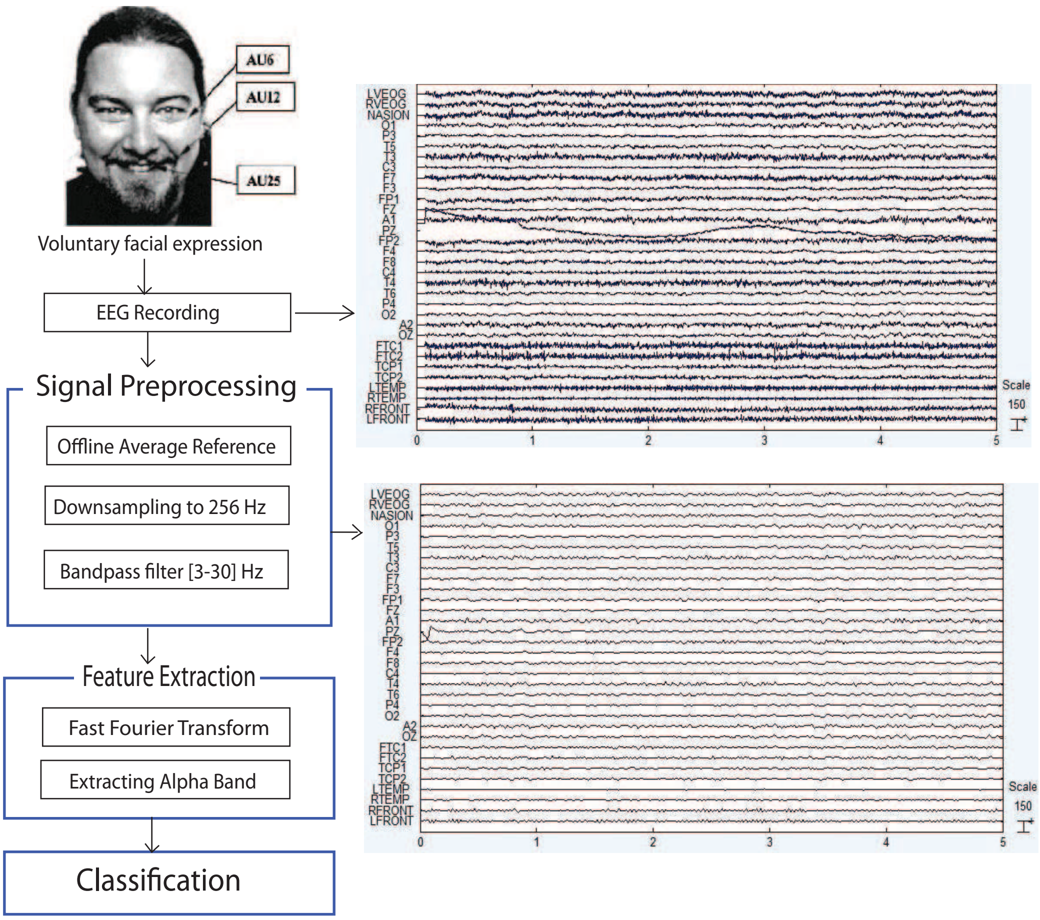

Figure 5.1: Multistage approach for emotion detection using EEG.

of rejecting such segments, we included them in our analysis so that our approach can be generalized to real time applications. Since most of the previously mentioned artifacts appear in low frequencies and because line noise appear in 50-60 Hz, we used a band pass finite impulse response filter that removed the frequencies below 3 Hz and above 30 Hz.

5.1.2 Feature Extraction and Reduction

Feature extraction is the process of selecting features that are representative to the emotion detection task. We started by extracting large number of features and then we started reducing such features in the feature reduction stage by selecting more distinctive features for the emotion detection task.

5.1.2.1 Feature Extraction

Our approach divides each 30 sec data epoch into 29 windows, 2 seconds wide with a sec overlapping window. Each window is converted into the frequency domain using Fast Fourier Transform (FFT). The frequency descriptors of the power bands, theta, alpha and beta rhythms, were extracted. This resulted in a huge feature set of 145000 features that is computed as

# of features = (# windows x # electrodes x # features per window)

- # windows, taking the whole 30 second epoch and dividing it into a 2 second window with 1 second overlap, will result into 29 windows.
- # electrodes, we used the whole 25 electrodes that are placed over all the regions of the scalp.
- # features per window, we extracted 100 frequency descriptors that represent the power band of the delta, theta, alpha, beta and gamma rhythms. We also, extracted 100 phase angle features that represent the same bands. we also extracted 5 heuristic features such as mean power, mean phase angle, peak magnitude, the frequency with the highest magnitude and number of frequency descriptors that are more than zero.

This will result in 205 features per window which resulted in approximately 145000 features.

5.1.2.1 Feature Reduction

After the feature extraction stage, we found out that our feature vector was of size 145000. We used two techniques for feature reduction a. using the alpha band only and b. making use of the scalp asymmetries that are associated with positive and negative emotions.

a. Feature Reduction Using Alpha Band

We made use of the study made by Kostyunina et al. [1] in order to reduce our feature set. Kostyunina et al. [1] showed that emotions such as joy, aggression and intention result in an increase in the alpha power whereas, emotions such as sorrow and anxiety results in a decrease in the alpha power. As a result of this conclusion, we focused our feature extraction on the power and phase of the alpha band only which ranges from 8 Hz to 13 Hz for the 25 electrodes. We used other features such as the mean phase, the mean power, the peak frequency, the peak magnitude and the number of samples above zero. Making use of the study made by Kostyunina et al. [1] helped in decreasing the number of features from 145000 to 10150 features, 14 (feature/window) x 29 (window/electrode) x 25 (electrodes) = 10150. The 14 features in each window include the 7 feature descriptors and 7 phase angles in the alpha band only.

b. Feature Reduction Using EEG Scalp Asymmetries

Another important research that we made use of in order to reduce our feature set is the research done by Coan et al. [25]. Coan et al. [25] showed that positive emotions are associated with relatively greater left frontal brain activity whereas negative emotions are associated with relatively greater right frontal brain activity. They also showed that the decrease in the activation in other regions of the brain such as the central, temporal and mid-frontal was less than the case in the frontal region. This domain specific knowledge helped us in decreasing the number of features from 10150 to only 2233 features, 7 (feature/window) x 29 (window/electrode) x 22 (electrodes) / 2 (asymmetry) = 2233. The 7 features include the alpha descriptors only without the phase angle. The reason why we used 22 electrodes only because we need to include symmetric electrodes only. For instance, F7 and F8 are symmetric with resect to the center of the brain. So There are not symmetric electrodes for 3 out of the 25 electrodes.

The asymmetry features between electrodes i and j at frequency n are obtained using

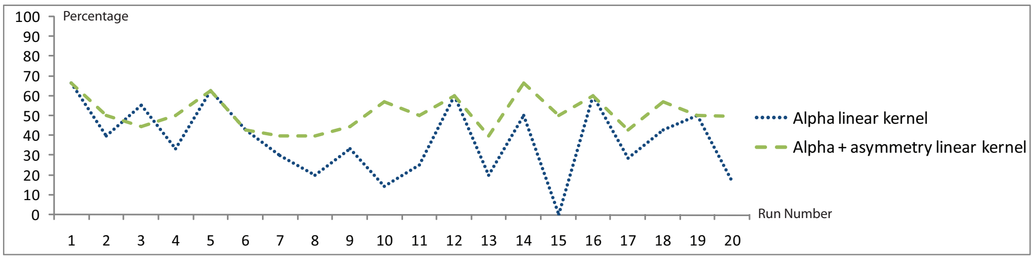

Figure 5.2: A comparison of the classification accuracy of joy emotion using a linear SVM kernel on two different feature selection criteria.

the following equation

$$c(n,i,j) = X_i(f_n) - X_j(f_n)$$

in which $X_i(f_n)$ is the frequency power at electrode i and the nth bin. This equation is applied to scalp symmetric electrodes only such as (C3, C4), (FP1, FP2)...etc.

5.1.3 Classification

For classification, we used support vector machines (SVMs). In case of a joy classifier, for instance, the samples are divided into two sets of samples, samples representing joy and samples representing not joy. The SVM classifier is trained on the extracted and reduced features. SVM will construct a separating hyperplane in that space that maximizes the margin between the two data sets, the set that represents joy and the set that represents not joy. A good hyperplane will be the one that has the highest distance to different points in different classes [47].

We built six different binary classifiers. For each emotion, we used

- two Linear SVM classifiers, one Linear classifier trained on the alpha band only and the second Linear classifier is trained on the scalp asymmetries features.
- two polynomial SVM classifiers, one polynomial classifier trained on the alpha band only and the second polynomial classifier is trained on the scalp asymmetries features.
- two radial SVM classifiers, one radial classifier trained on the alpha band only and the radial second classifier is trained on the scalp asymmetries features.

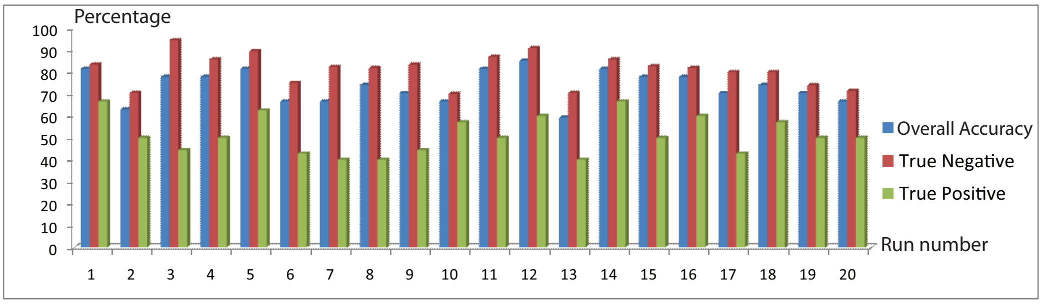

Figure 5.3: Classification accuracy of the joy classifier. True positive, True Negative and overall classification accuracy of the joy classifier on 20 different runs using a linear SVM kernel on the (alpha band + asymmetry) feature set.

5.2 Experimental Results

Using the database collected by [25], the experiment included 36 participants with 265 samples (66 samples representing joy, 64 samples representing sadness, 65 samples representing fear and 70 samples representing anger). Our experiments started by trying to detect the four different emotions, anger, fear, joy and sadness. After succeeding in this task, we started to investigate the process of reducing the number of electrodes against the detection accuracy of the for emotions.

5.2.1 Detecting Four Different Emotions

We started by building a joy emotion classifier on which all the samples representing joy are considered positive samples and all other samples represent negative samples. Six different classifiers were built, two classifiers with linear kernel for each set of features, two classifiers with radial kernel for each set of features and two classifiers with polynomial features for each set of features. The SVM classifiers with polynomial did not converge whereas the classifiers with radial kernel resulted in a very low accuracy of almost 0 %. To test our classifiers, we used 20-fold cross validation in which we divided our 265 samples into testing samples (10%) and training samples (90%) which means that the samples we used for training are different from those used for testing. We repeated this approach 20 times during which the testing and training samples were selected randomly and we made sure that the training and testing samples are different in the 20 trials. Fig. 5.2 compares the true positive of the joy emotion classifier using a linear SVM kernel on two different feature selection criteria. We found out that the use of the alpha band combined

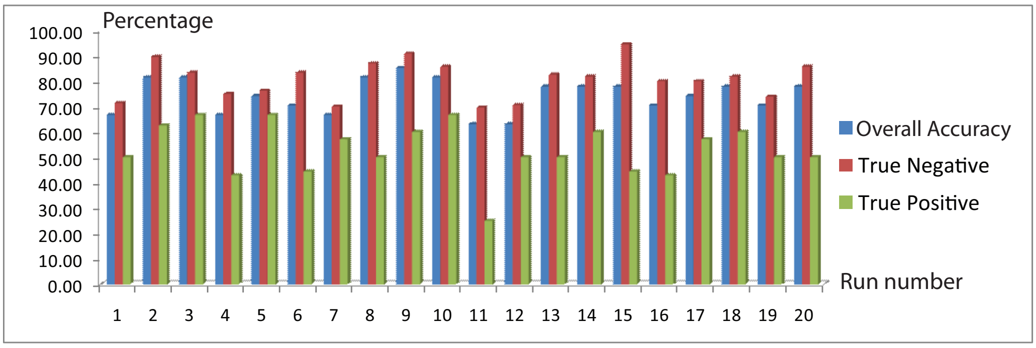

Figure 5.4: Classification accuracy of the anger classifier. True positive, True Negative and overall classification accuracy of the anger classifier on 20 different runs using a linear SVM kernel on the (alpha band + asymmetry) feature set.

with EEG scalp difference resulted in a better detection accuracy than using the alpha band only. This again proves that using neuroscience findings in feature selection helps in decreasing the size of the feature set and results in better classification accuracies. Also, we found out that the radial kernel for both types of features resulted in 0 % accuracy for joy and in a very high classification accuracy of almost 100% for the not joy emotion. This can show that our samples are linearly separable. The average detection accuracy is 51% and 83% for the presence of joy and not joy emotion respectively using linear kernel.

Fig. 5.3 shows the overall classification accuracy, average detection accuracy of the presence of the joy, true positive, and the average detection accuracy of the absence of the joy emotion, true negative, using a linear SVM kernel. The overall classification accuracy represents the number of correctly classified samples that represent joy or not joy divided by the total number of testing samples which is 27 samples, 10% of the total number of samples. The true positive of joy is the number of correctly classified samples that represent joy divided by the total number of joy samples in the testing set. Finally, the true negative is the number of correctly classified samples that represent not joy divided by the total number of not joy samples in the testing set. Table 5.1 represents the confusion matrix for the joy emotion classifier. The upper left cell represents the true positive, the upper right cell represents the false positive, the lower left cell represents the false negative and the lower right cell represents the true negative. From Table 5.1, we can find that the precision is 65/(65+63) = 50.7 %, recall is 64 / (65+79) = 45.13% and accuracy is (65+333)/(65+63+79+333) = 73.7%. Precision is a measure of exactness or fidelity, whereas Recall is a measure of completeness. Precision for a class is the number of true

Table 5.1: Confusion Matrix for the joy emotion classifier using (alpha + asymmetry) feature set.

		Actual	
		True	False
Predicted	True	65	63
	False	79	333

Table 5.2: Confusion Matrix for the anger emotion classifier using (alpha + asymmetry) feature.

		Actual	
		True	False
Predicted	True	65	57
	False	81	337

positives or the number of items correctly labeled as belonging to the positive class divided by the true positive plus the false positive. Recall is the number of true positives divided by the total number of elements that actually belong to the positive class or the sum of true positives and false negatives, which are items which were not labeled as belonging to the positive class but should have been. Accuracy is the sum of true positive and true negative divided by the sum of true positive, true negative, false positive and false negative.

We applied the same approach for building classifiers for anger, fear and sad emotions. Fig. 5.4, Fig. 5.5, Fig. 5.6 shows the classification accuracies of the linear SVM kernel for the (alpha + asymmetry) feature sets for anger, fear and sad emotions respectively. From table 5.2, table 5.3 and table 5.4, we can find out that the precision values are 53.3%, 53.3%, 50%, the recall values are 44.5%, 39%, 45.8% and accuracy values are 74.5%, 71%, 77.8% for anger, sadness and fear respectively.

The reason why the accuracies of anger, fear, joy and sadness range from 30% to 72.6% can be explained by the fact that voluntary facial expressions may affect the emotional state of people differently and with different intensities. Coan and Allen [48] who experimented on the same dataset, reported that the dimensions of experience vary as a function of specific emotions and individual differences when compared self reports against the intended emotions to be elicited with certain facial expressions. Table 5.5 shows the report rates for different emotions. Table 5.5 can show that self reports were different from the

Table 5.3: Confusion Matrix for the sad emotion classifier using (alpha + asymmetry) feature set.

		Actual	
		True	False
Predicted	True	64	56
	False	101	319

Table 5.4: Confusion Matrix for the fear emotion classifier using (alpha + asymmetry) feature set.

		Actual	
		True	False
Predicted	True	55	55
	False	65	365

Table 5.5: Self Report Rates by Emotion. The rate column reflects the percentage that self reports were the same as the target emotion.

Emotion	Rate
Anger	65.7%
Fear	61.8%
Joy	50.0%
Sadness	30.6%
Overall Average	52.0%

intended emotions in 48% of the samples. In this work, we did not ignore the samples for which self reports did not match the elicited emotions. It may have increased the accuracy if we used the samples for which the participants have felt and reported the same emotion as the intended one. Also, the accuracy may be affected if the samples used are the ones that the participants reported the emotions with high intensities. Table 5.6 shows a comparison of the average detection accuracy for the four emotions. For each emotion, we are reporting the results of the linear SVM kernel on two feature sets, using the alpha band only and using the alpha band along with scalp asymmetries. For each feature set, the percentage of presence of joy, for instance, is computed as:

$$(\sum_{i=1}^{N} F(i)) * 100/N$$

where F(i) is 1 if the joy sample number i was correctly classified and 0 otherwise. N is the number of all the joy samples in the 20 different runs. The overall accuracy is the

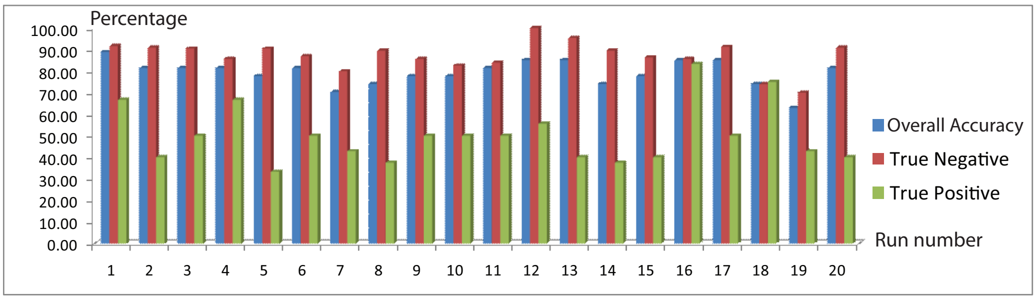

Figure 5.5: Classification accuracy of the fear classifier. True positive, True Negative and overall classification accuracy of the fear classifier on 20 different runs using a linear SVM kernel on the (alpha band + asymmetry) feature set.

Table 5.6: Results of emotion classification using linear SVM kernels on two different feature sets: using the alpha band only and using scalp asymmetries.

Emotion	Alpha			Alpha + asymmetry		
	presence	absence	overall	presence	absence	overall
Anger	38%	83%	73%	53%	81%	74%
Fear	58%	87%	79%	38%	87%	77%
Joy	38%	87%	73%	51%	81%	74%
Sadness	48%	78%	77%	61%	75%	79%

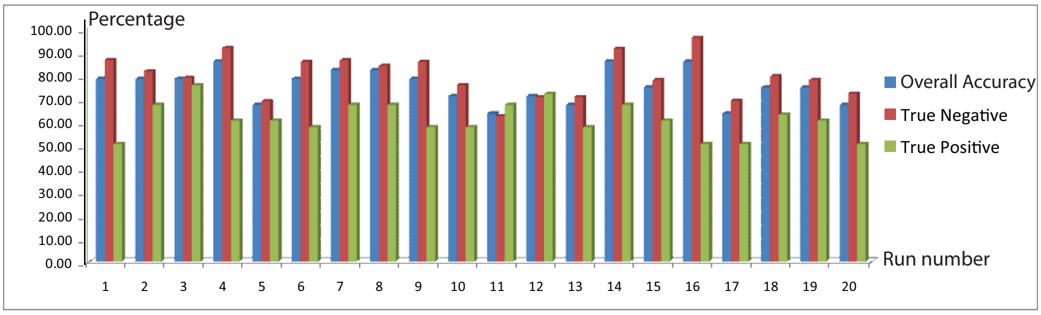

Figure 5.6: Classification accuracy of the sadness classifier. True positive, True Negative and overall classification accuracy of the sadness classifier on 20 different runs using a linear SVM kernel on the (alpha band + asymmetry) feature set.

number of samples whether it is joy or not joy that are correctly classified divided by the total number of samples in the 20 different runs.

It is observed that the accuracy of the linear kernel for the second feature set (alpha + asymmetry) is higher than the linear kernel for the first feature set (alpha band only) in joy, anger and sad emotions. Whereas, the detection accuracy for the linear kernel for the first feature set (alpha band only) is higher in the fear emotion than the linear kernel of the second feature set (alpha + asymmetry).

5.2.2 Reducing the Number of Electrodes Vs Accuracy

All the previous experiments for detecting the four emotions made use of 25 electrodes that are spread all over the scalp which are O1, P3, T5, T3, C3, F7, F3, FP1, FZ, A1, PZ, FP2, F4, F8, C4, T4, T6, P4, O2, A2, OZ, FTC1, FTC2, TCP1 and TCP2 except for the experiments that made use of scalp asymmetries for dimensionality reduction in which we used only 22 electrodes, O1, P3, T5, T3, C3, F7, F3, FP1, A1, FP2, F4, F8, C4, T4, T6, P4, O2, A2, FTC1, FTC2, TCP1 and TCP2. The problem with using large number of electrodes is that it becomes not convenient for integration in real life situations and results in huge processing time.

For more convenience, better usability and easier integration in real life applications, we decided to explore the possibility of decreasing the number of electrodes against the

Table 5.7: Selected electrodes while applying our approach with fewer number of electrodes.

# of electrodes	electrodes with frontal included	electrodes with frontal not included	# of features
16 electrodes	F3, F4, FP1, FP2, F7, F8, FTC1, FTC2, C3, C4, O1, O2, T3, T4, P3, P4	O1, O2, P3, P4, C3, C4, T3, T4, T5, T6, TCP1, TCP2, FTC1, FTC2, F3, F4	1624
12 electrodes	F3, F4, FP1, FP2, F7, F8, FTC1, FTC2, C3, C4, O1, O2, T3, T4	O1, O2, P3, P4, C3, C4, T3, T4, T5, T6, TCP1, TCP2	1218
8 electrodes	F3, F4, FP1, FP2, F7, F8, FTC1, FTC2	O1, O2, P3, P4, C3, C4, T3, T4	812
6 electrodes	F3, F4, FP1, FP2, F7, F8	O1, O2, P3, P4, C3, C4	609
4 electrodes	F3, F4, FP1, FP2	O1, O2, P3, P4	406

detection accuracies of the four emotions. According to Kostyunina et al [1], emotions are most obvious in the alpha band and the alpha band is most obvious in the frontal and occipital lobes. Also, emotions may be obvious in central and temporal regions. So, our priority was selecting the electrodes placed on the frontal lobe then the occipital then the central-parietal and finally the temporal lobe. However, noise resulting from facial expressions affect the EEG signals captured from the frontal lobe. Consequently, we decided to use two different approaches in reducing the number of electrodes. The first approach is to select the electrodes while including those placed on the frontal lobe. The second approach is to ignore the electrodes placed on the frontal lobe to see whether the noise resulting from the facial expressions affect the classification accuracies. We experimented with 16, 12, 8, 6 and 4 electrodes.

Table 5.7 shows the selected electrodes on both approaches. The second column shows the electrodes selected when using frontal lobe electrodes. The third column shows that all the selected electrodes do not include any frontal electrodes. For example, in the last row when we included frontal electrodes, the whole four electrodes were selected from the frontal lobe, F3, F4, FP1 and FP2. On the contrary, when we decided not to include frontal lobe electrodes, the four selected electrodes were from the occipital and parietal regions, O1, O2, P3 and P4. The last column of Table 5.7 shows the number of feature set used in the classifier that uses both the alpha and scalp asymmetries. The number of features is computed as

# of features = (29 (windows) x num of electrodes x 7 features) / 2 (for asymmetry)

We experimented with the two feature sets. However, since using the alpha band along with scalp asymmetries resulted in higher detection accuracies of the four emotions and fewer features than using alpha band only, we decided not to include some relevant electrodes such as Fz or Oz because these electrodes are placed on the center of the scalp and there are no electrodes that are symmetric with such electrodes.

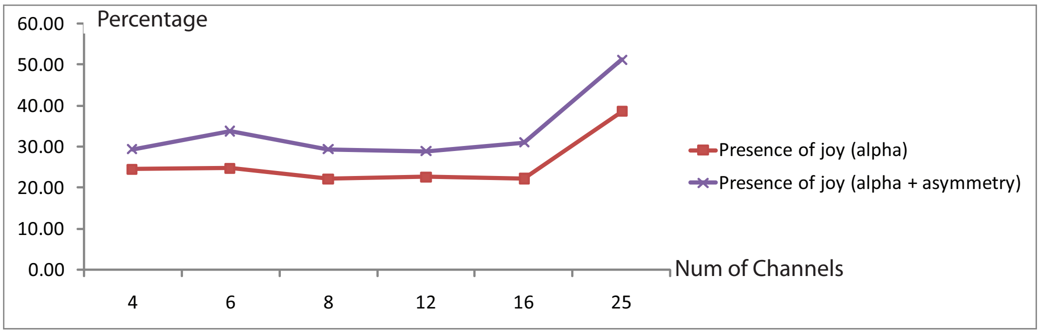

Figure 5.7: A comparison of the classification accuracy of joy emotion while changing the number of electrodes while not including the frontal electrodes.

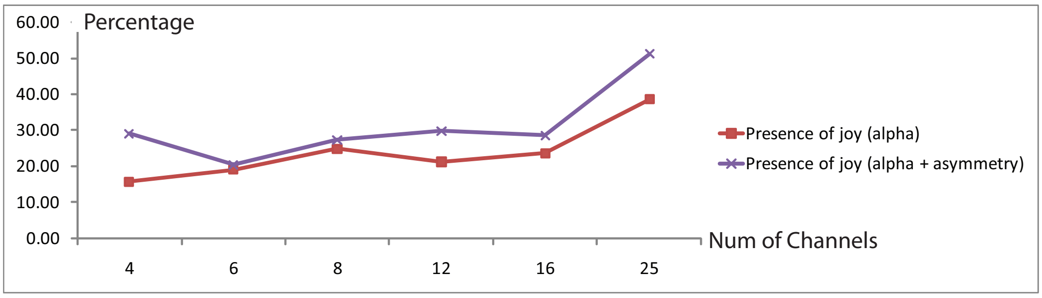

Figure 5.8: A comparison of the classification accuracy of joy emotion while including the frontal electrodes.

We used the same 20 training and testing sets used in our previous experiments while using 25 electrodes. We computed the average detection accuracy of both the presence of joy and absence of joy. Fig. 5.7 and Fig. 5.8 shows the average classification accuracies of the presence and absence of joy using the two feature sets using different number of electrodes.

It was predicted that as the number of electrodes decreases the detection accuracy decreases. However, there is a slight decrease in the detection accuracies among the 16, 12 and 8 electrodes in both Fig. 5.7 and Fig. 5.8. This can show that temporal lobe electrodes such as TCP1, TCP2, T5 and T6 have little effect on the classification accuracy. Also, it can be observed from Fig. 5.8 that using four electrodes results in a slight increase in the detection accuracy more than 6 and 8 electrodes when using the alpha and scalp asymmetries as feature set. This is because the only four electrodes used are all fontal lobe electrodes. Consequently, we can deduce that EMG has a little effect on our reported accuracy because part of this increase in accuracy is because alpha rhythm is more obvious in the frontal lobe. On the other hand, In case of Fig. 5.7, using 6 electrodes results in a slight increase in the accuracy more than using 8 electrodes. So we can deduct

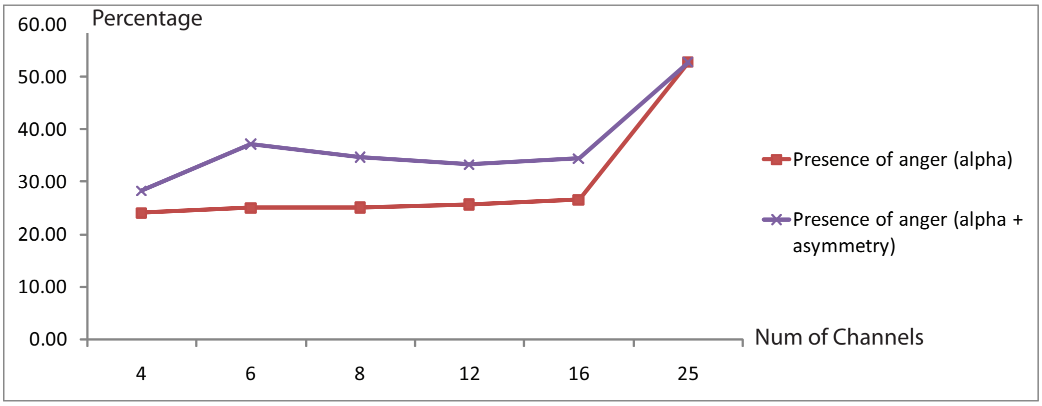

Figure 5.9: A comparison of the classification accuracy of anger emotion while not including the frontal electrodes.

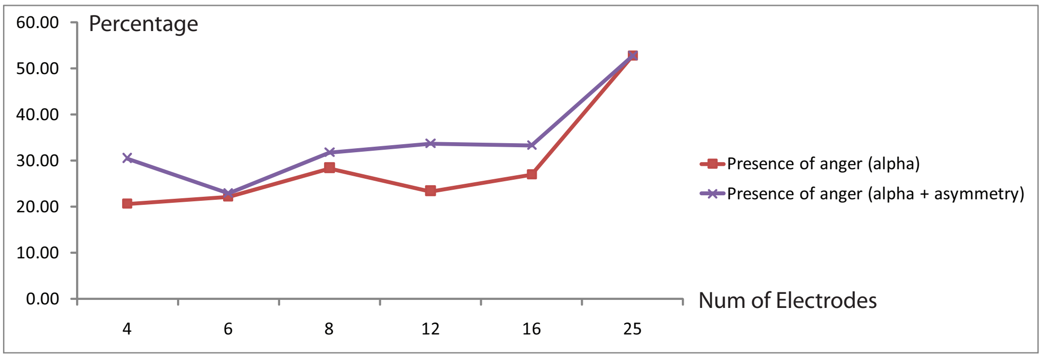

Figure 5.10: A comparison of the classification accuracy of anger emotion while including the frontal electrodes.

that temporal lobe electrodes are less effective in the classification task than the central, parietal and occipital lobes since the experiments using 8 electrodes contained the same electrodes as the 6 electrodes experiments plus two temporal electrodes which are T3 and T4.

We applied the same approach to anger, sad and fear emotions. Fig. 5.9 and Fig. 5.10 shows the classification accuracy versus number of electrodes for anger emotion. Fig. 5.11 and Fig. 5.12 shows the classification accuracy versus number of electrodes for sad emotion. Fig. 5.13 and Fig. 5.14 shows the classification accuracy versus number of electrodes for fear emotion.

Fig. 5.9 and Fig. 5.10 show the same trend as Fig. 5.7 and Fig. 5.8 in which there is a slight improvement in the classification accuracy when 6 electrodes are used with the absence of frontal lobe electrodes than 8 electrodes. Also, using only 4 frontal electrodes results in a better classification accuracy as shown in Fig. 5.10.

Fig. 5.11 and Fig. 5.12 also show a similar trend as Fig. 5.7 and Fig. 5.8 in using only

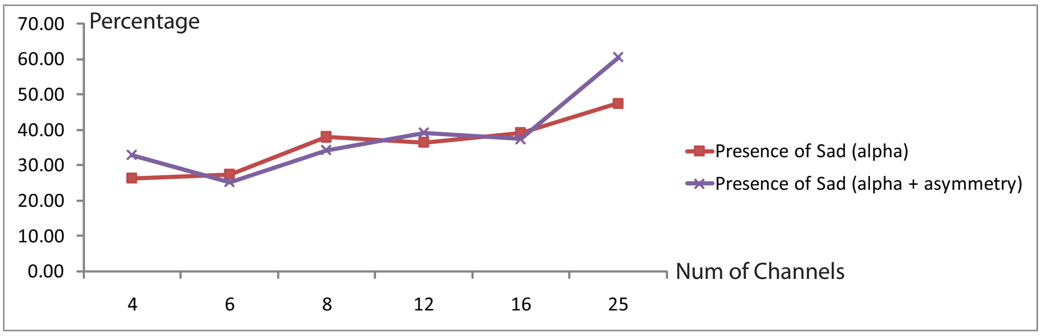

Figure 5.11: A comparison of the classification accuracy of sad emotion while not including the frontal electrodes.

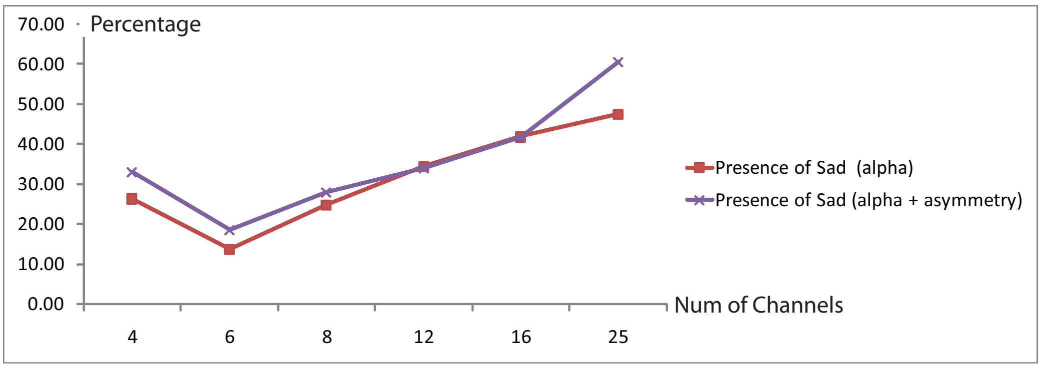

Figure 5.12: A comparison of the classification accuracy of sad emotion while including the frontal electrodes.

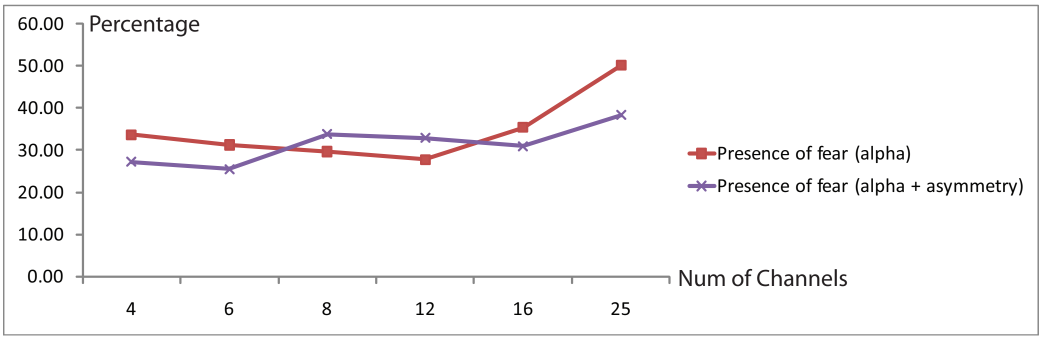

Figure 5.13: A comparison of the classification accuracy of fear emotion while not including the frontal electrodes.

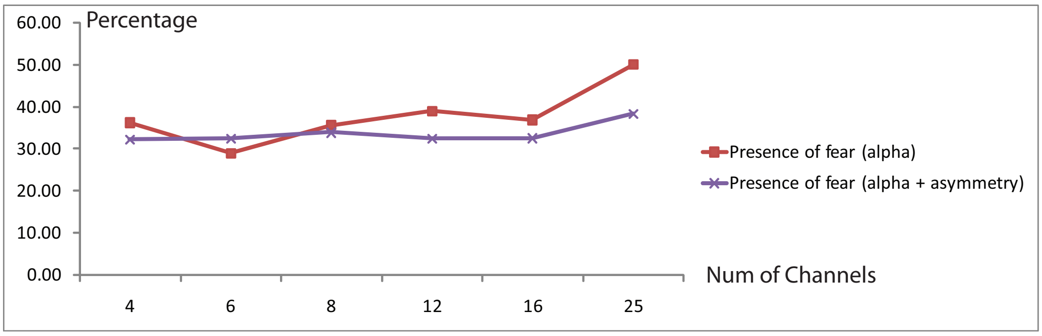

Figure 5.14: A comparison of the classification accuracy of fear emotion while including the frontal electrodes.

4 frontal electrodes results in a better classification accuracy as shown in Fig. 5.12.

Finally in Fig. 5.13 and Fig. 5.14, we found out that using alpha band only results in a better classification accuracy than using both the alpha band and scalp asymmetries. it is observed from Fig. 5.13 and Fig. 5.14 that using only 4 frontal electrodes results in a better classification accuracy than using 6 or 8 electrodes which is the same observation for the other three emotions.

The most reasonable number of electrodes is 6 electrodes in case the electrodes placed on the frontal lobe are not included and 4 electrodes in case the electrodes placed on the frontal lobe are included. This is because 4 or 6 electrodes are convenient, results in acceptable classification accuracy around 34 % using the (alpha + asymmetry) feature set for sad, joy and anger emotions and using the first feature set in case of fear.

We tried to acquire EEG data using the available g.Mobilab hardware from g.tech. However, the acquisition device is not advanced enough for this task and the environment was not great for acquiring emotion related EEG data. So we were not able to get quality EEG signals. Also, we used BCI2000 as an acquisition software as it implements the driver for the g.Mobilab hardware. The problem we faced is that BCI2000 does not offer a technique for starting the acquisition at a desired time. For instance, we want to start the software and give it an automated trigger from our application on when to start acquiring EEG data from the hardware. This is not the case which means that we do not have any log at the time during which the emotional state started which hinders using such software.

Our main contribution is shown to be in the experimental methodology applied for building an automated system for emotion detection. First we experimented with a totally new elicitation technique that is very close to real life situations. Second, We are also generating totaly different feature sets from the prior art and comparing the accuracies of different classifiers that use such different feature sets. Finally, we experimented with different number of electrodes that were selected using two different methodologies.

Our main contributions are that we are the first in the computer science field to use voluntary facial expression as a means for enticing emotions. Although this contaminates EEG with noise, it helps to test our approach on unconstrained environment where the users were not given any special instructions about reducing head motions or facial expressions which makes our dataset close to a real time application.

Also, we used a new method for selecting features that are relevant to the emotion detection task that is based on neuroscience findings. Third, since one of the drawbacks of emotion detection systems using EEG is the use of large number of electrodes, which hinders the portability of such systems, we applied our approach on different number of electrodes that range from 4 electrodes up to 25 electrodes using two methodologies for selecting the electrodes to be eliminated. The first of which was to include the frontal and occipital electrodes because the scalp asymmetries are most obvious the frontal lobe whereas, the alpha band is most obvious in the occipital region. The second approach is to avoid using the frontal lobe electrodes because the EMG produced from facial expressions affect the frontal EEG recordings. So we wanted to make sure that the results we are getting are mainly because of the EEG and not EMG.

Using fewer number of electrodes with reasonable accuracy can make our system more portable and can be used in real application. We tested our approach on a large dataset of 36 subjects and we were able to differentiate between four different emotions with an accuracy that ranges from 51% to 61% using 25 electrodes and we reached an average classification accuracy of 33% for joy emotion, 38% for anger, 33% for fear and 37.5% for sadness using 4 or 6 electrodes only.

Chapter 6

Conclusion and Future Directions

6.1 Conclusion

The goal of this research is to study the possibility of classifying four different emotions from brain signals that were elicited due to voluntary facial expressions. We proposed an approach that is applied on a noisy database of brain signals. Testing on large corpus of 36 subjects and using two different techniques for feature extractions that rely on domain knowledge, we reached an accuracy of 53%, 58%, 51% and 61% for anger, fear, joy and sadness emotions respectively.

Studying emotions is important because emotions are fundamental to human experience, influencing cognition and affecting rational decisions. Researchers are trying to build systems that can detect emotions automatically to be integrated into various applications such as software adaptation in which the software user interface can change and provide help to users based on their emotional state. Another important application is monitoring safety critical systems. For instance, monitoring the emotional state of pilots and astronauts can help providing them with support during periods of stress where their decision may be negatively affected by their emotional state.

Building automated systems for capturing humans' emotional states have been the focus of computer scientists during the last two decade. Scientists tried to use different channels for emotion detection. Channels such as facial expressions and voice processing have showed a great success. However, the main drawback of using facial expressions or speech recognition is the fact that they are not reliable indicators of emotion because they can either be faked by the user or may not be produced as a result of the detected emotion. Scientists started to use new channels such as involuntary physiological signals such as heart beats, temperature, skin conductance and blood pressure to infer emotions. The problem with such channel is that it requires using sensors in various parts of the body which makes it not comfortable.

Another channel for emotion detection is using brain signals recorded using EEG. Few research have been done to make use of EEG as a new channel for emotion detection. The problem with most the previous research is that they used large number of electrodes that range from 32 to 64 electrodes which increase the processing time and make it not comfortable for users to be used in real applications. Also, researchers use auditory or visual stimulus for emotion elicitation while asking the users to reduce any motion and facial expressions in order not to contaminate EEG signals with noise. This is problematic because in real applications there are no constraints on the users' environment which result in highly contaminated EEG signals.

Instead of using a visual or an auditory stimulus for emotion elicitation, we are the first in the computer science field to use voluntary facial expression as an elicitor for four emotions, anger, fear, joy and sadness. Voluntary facial expressions are based on the facial feedback paradigm which shows that facial expressions are robust elicitors of emotional experience. Although this contaminates EEG with noise, it helps to test our approach on unconstrained environment where the users will not be given any special instructions about reducing head motions or facial expressions. We used 25 electrodes that are scattered on different regions on the surface of the scalp for EEG recording.

We used a new method for selecting features that are relevant to the emotion detection task that is based on neuroscience findings. We made use of the findings made by Kostyunina et al. [1]. Kostyunina et al. [1] showed that emotions such as joy, aggression and intention result in an increase in the alpha power whereas, emotions such as sorrow and anxiety results in a decrease in the alpha power. As a result of this conclusion, we focused our feature extraction on the power and phase of the alpha band only which ranges from 8 Hz to 13 Hz for the 25 electrodes. We are also, making use of the findings made by Coan et al. [48]. Coan et al. [48] showed that positive emotions are associated with relatively greater left frontal brain activity whereas negative emotions are associated with relatively greater right frontal brain activity. They also showed that the decrease in the activation in other regions of the brain such as the central, temporal and mid-frontal was less than the case in the frontal region. This domain specific knowledge helped us in decreasing the number of features in our feature set dramatically.

Finally, since one of the drawbacks of the previous work is the use of large number of electrodes which hinders the portability of such systems, we applied our approach on different number of electrodes that range from 4 electrodes up to 25 electrodes. This can make our system more portable and can be used in real applications.

Our approach analyzes highly contaminated EEG data produced from a new emotion elicitation technique. We make use of two new feature selection mechanisms that help to extract features that are more relevant to the emotion detection task. We reached a true positive of 51% for joy emotion, 53% for anger, 53% for fear and 50% for sadness. The overall classification accuracy is 73.7% for joy emotion, 75.4% for anger, 71% for fear and 77.8% for sadness. Also, we tested the same approach on a fewer number of electrodes from 25 electrodes down to 4 electrodes only.

We used two techniques for reducing the number of electrodes. In the first technique, we kept the electrodes in the frontal lobe because the alpha band is most obvious in the frontal lobe. In the second technique, we removed the electrodes that were placed in the frontal lobe in order to make sure that the results we are getting are not affected by EMG signals due to facial expressions. We found out that as the number of electrodes decreases the accuracy decreases. This was expected but we reached a reasonable accuracy at only 4 and 6 electrodes. We reached an average accuracy of 33% for joy emotion, 38% for anger, 33% for fear and 37.5% for sadness. We also, found out that the accuracy of using frontal lobe electrodes is slightly higher than the accuracy without them. This can be explained by the fact that the alpha band is most obvious in the frontal lobe and the noise due to the facial expressions may have a very slight effect on the classification accuracy.

Finally, we would recommend our approach to be used in real life situations. The training phase is most time consuming as SVM training requires time between O(N^2 + N*D) and O(N^3 + N*D) where N is the number of support vectors and D is the number of dimensions. The testing time complexity is the time for O (signal preprocessing + feature extraction + selecting relevant features + SVM classification). Although finite impulse response filters usually take O(k*M^2), an implementation of the signal preprocessing provided in [49] requires only O(k*M) where M is the length of the batch and k is the number of electrodes. FFT requires O(n*lgn) where n is the number of points which is 29 windows * 2 seconds * 256 samples, selecting relevant features requires O(c). SVM classification requires O(N) where N is the number of support vectors. So the overall time complexity for the testing is the maximum of O(n*lgn) and O(k*M).

6.2 Future Directions

One way to achieve a better classification results is to improve our preprocessing stage. This can be done by using Independent Component Analysis (ICA). ICA is a computational model that can extract the different components of the signals. For instance, ICA can separate EEG and physiological noise from the recorded signals. The problem with ICA is that it separates the two signals without showing which signal represents the noise and which signal represents the EEG recording. Scientists usually use heuristic based approaches to infer which signal represents the EEG recording.

Another important area of research that this thesis opens is how to modify the elicitation technique to help the participants better feel the desired emotion. It would be interesting to remove the samples that have different self reports from the desired emotion and study that effect on the classification accuracy. The problem with our dataset is the presence of only 265 samples. If we removed the samples with different self reports, we will end up with only 150 samples.

It would be also, important to apply the same technique on a database of emotion elicited using both the stimulus and imagination techniques. This will help us make sure that our approach generalizes on different elicitation technique which is important to ensure that our approach can run successfully in real life situations.

Finally, our approach needs to be tested on real situations using the 7 electrode cap of UCSD or the 16 electrode cap from Emotiv. If it worked with reasonable accuracy, this may open the door for integrating emotion detection using EEG in lots of important applications.

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