ANALYSIS OF PHYSIOLOGICAL PARAMETERS FOR COGNITIVE ENHANCEMENT

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree

of

MASTER OF TECHNOLOGY

in

ELECTRICAL ENGINEERING

(With Specialization in Instrumentation and Signal Processing)

By

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DEDICATION

This thesis is dedicated to my dear family: Maa, Papa, Prashant, Lokesh and, Noor.

CORONA NON SINE LABORE

(No crown without hard work)

No. – MT/255/V.K/A.S/2013

CANDIDATE'S DECLARATION

I hereby declare that the work presented in this dissertation entitled **"ANALYSIS OF PHYSIOLOGICAL PARAMETERS FOR COGNITIVE ENHANCEMENT"** submitted in partial fulfillment of the requirement for the award of the degree of **Master of Technology** with specialization in **Instrumentation and Signal Processing**, in the **Department of Electrical Engineering, Indian Institute of Technology, Roorkee** is an authentic record of my own work carried out from June 2012 to June 2013 under the guidance and supervision of **Prof. Vinod Kumar** and **Dr. Ambalika Sharma**, Department of Electrical Engineering, Indian Institute of Technology Roorkee.

I have not submitted the matter embodied in this dissertation report for the award of any other degree or diploma.

Date: 14/6/13

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CERTIFICATE

This to certify that the above statement made by the candidate is true to the best of my knowledge and belief.

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ABSTRACT

Emotions are considered to be an important part of our life; they affect each and every aspect of life. Emotions are perceived by peripheral nervous system and processed in the brain and accordingly action is produced through muscle movement, facial expression, body temperature and all. In the brain, cerebrum or precisely somatosensory cortex is considered to be the emotion processing center. The following study was designed to study the electrical activation occurring in the rhythmic bands of electroencephalograph (EEG) during audio-visual stimuli. Audio-visual stimuli consists of 10 videos, two each from different categories, viz. fear, anger, funny, sad and, neutral emotional video clips. The video clips were again divided in two categories one having low intensity of emotion and second having high intensity of emotion. Their affective valence was unpleasant, neutral or pleasant, while affective arousal was calm, neutral or excited.

Twenty right handed participants were made to watch emotional video clips. EEG and ECG were recorded simultaneously while watching video clips for 10 channels and 3 channels respectively. The videos were played in such an order so that video having low emotional intensity content is played first and the one having high intensity emotions are played afterwards. The Gamma, Beta, Alpha, Theta and, low Alpha rhythmic frequency bands were extracted from EEG and the average power was computed using FFT. In ECG, RR intervals were extracted and mean RR interval was computed for HRV analysis.

Finally, after analysis it is revealed that for fear and funny video stimuli, the EEG rhythmic band average power decreases on increasing emotional intensity in the videos, for all 10 channels over the scalp. For anger video stimuli, the EEG rhythmic band average power increases on increasing the emotional intensity in all channels except over prefrontal and central lobe. For sad emotion video stimuli, the EEG rhythmic band average power decreases on increasing the emotional intensity in all channels except over temporal and occipital lobe. In HRV analysis it is revealed that the RR interval decreases when a subject go through any emotion as compared to normal conditions. The anger video stimuli shows lowest RR interval and fear emotions show highest RR interval values, within emotion subset. Summing up, these results demonstrate that the variations are noted for different emotions.

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ACRONYMS

EEG	Electroencephalogram
ECG	Electrocardiogram
HRV	Hear Rate Variability
HCI	Human Computer Interface
BCI	Brain Computer Interface
ER	Emotion Recognition
HMI	Human Machine Interface
ALS	Amyotrophic Lateral Selerosis
CBT	Cognitive Behavior Therapy
PFC	Prefrontal Cortex
fMRI	Functional Magnetic Resonance Imaging
EMG	Electromyogram
UIM	Universal Interface Module
EDA	Electrodermal activity
ERP	Event Related Potential
CNS	Central Nervous System
PET	Positron Emission Tomography
EOG	Electrooculography

CHAPTER 1

INTRODUCTION

From past few decades, Human-Computer Interface (HCI) has attracted large attention from scientist and engineers. Efforts are made to make computer more than just a computational device, immense research have been done in this field, to make computer more interactive with humans [1][2][5][6]. Computer is now viewed as communicating machine, socializing gadget, shopping and fun device. Thus computerized systems are seen everywhere in day to day life from remote monitoring of plant to imparting education to remote monitoring of patients [7][8][9]. User interaction with online social platforms, remotely patient or kids monitoring, and education can be made more interactive, if computer can understand emotions developed by end user while operating such platforms. Emotion is psycho-physiological process triggered by conscious and unconscious perception of object or situation. This is often associated with mood, temperature, environment, and past events. Emotions are one of the important factors in decision making, communicating and interacting with human beings. Emotion Recognition (ER) has gained intense attention in the last decade as the immense need of Human Machine Interface (HMI) has risen. HMI have dramatically influenced our lives in many aspects, such as, communication, entertainment and profession. Emotion Recognition plays an important role in Human-Human Interface (HHI). Considering large dependency of human being on machines, emotion interaction with machine is most important area in Human-Machine Interface (HMI) and Brain-Computer Interface (BCI). To make machines more efficient there is a need of making them capable of understanding human emotion without user translation. There are evidences from few experiments that HHI does not have significant difference from HMI [1]. If computer can itself understand emotional state of user, it would be easy to distinguish between likes and unlike of the population.

Several studies have been performed for automatic emotion detection. They can be divided into two categories. The first kind of approach is focused on face recognition or speech recognition [2][3][4]. The conventional emotion recognition approach, using facial expression and speech is user dependent and less accurate. The second kind of approach is focused on physiological signal analysis, in this, study is performed on bio-signals such as, EEG

(Electroencephalogram), ECG (Electrocardiogram), Skin conductance and so on. Researchers carried out huge amount of experiments to study what are the changes occurring in the physiological signal parameters while undergoing through different emotional states.


Figure 1.1: Example of BCI System
Image from www.bldesign.ch

Another application is emotion expression for people suffering from severe muscle diseases like Amyotrophic Lateral Sclerosis (ALS). These patients may not be able to move their muscles or to speak. Some progress is made in creating a brain-computer interface for those patients to enable them to communicate again. A way to express emotion would be a great improvement to such a system.

The objective of this thesis is *to explore changes during different emotional states based on subjective and subject independent analysis*. Emotion elicitation is performed by watching video clips. Subjective analysis is performed in order to estimate how different emotions contribute to brain region activation among different subjects. Subject Subject-independent analysis is performed in order to investigate the common behavior of all subjects and draw general conclusions on how brain is affected by emotions while watching music videos. The objective can be scattered in few other research questions:

1. *Are changes in cerebral cortex due to different emotional states can be recorded in EEG?*
   Literature suggests that changes in the cerebral cortex are noted in EEG. However, the results in practice show different result. In this work we are exploring the changes encountered in cerebral cortex as well as changes in Heart Rate Variability (HRV) during different emotion elicitation. We will create dataset with EEG and ECG signals which can be used to study changes in the parameters.
   a) *How to record EEG and ECG using hardware?*
      We will find out how to acquire EEG and ECG using Biopac® hardware and Acqknowledge software. Using that knowledge we will setup an experiment for EEG and ECG acquisition during emotion elicitation. These dataset will help in studying the changes happening in the cerebral cortex.

b) *How to process EEG and ECG data?*

Huge amount of data is collected during acquisition of EEG and ECG. This dataset contain brain activity as well as noise and artifacts. We have to process data, extracting required information like brain activity, HRV and, filtering out noise and artifacts.

c) *How to compute features of EEG and ECG signals?*

Computation of the features will be done. Features reflecting elicited emotions on different locations of the brain. The features with high variability will be kept and other would be discarded.

CHAPTER 2

BACKGROUND

Psychology, neuroscience, electrical engineering and computer science are all part of multidisciplinary approach to this thesis. Emotions, brain computer interface (BCI), affective science, electroencephalography (EEG) are all the fields that motivated this work to this extend and present for researchers and scientific society before moving into main chapters. A short description of these topics is provided in this chapter. This chapter will present basic theory, aim of the thesis, and literature background.

2.1 Cognitive Behavior Therapy

Cognitive behavior therapy (CBT) emerged in early 1960s [12]. Cognitive-behavioral therapy (CBT) is combination of two different fields, *cognitive theory and behavioral theory.* A T Beck is the founder of the Cognitive Behavioral Therapy. Two elements viz. cognitive therapy and the behavioral of CBT got blended in the near the beginning of 1960s [12]. Cognitive theory and behaviorism have different history, however around 1960's these two theories combined and the combination is popularly known to us as Cognitive Behavioral Therapy.

Behaviorism covers external behaviors and does not deal with the inner mental processes. CBT is a process of developing, grooming, and lifting the positive behaviors [13][14]. The classification of emotion and other mind states in the form of cognitive pattern is done in CBT.

CBTs responsible for three important factors

1. Behavior is affected by cognitive activity
2. Alteration and monitoring of cognitive activity is possible
3. Desired behavior change can be obtained by the cognitive change

2.1.1 Behavioural Theory

The behavioral component foundation of the CBT backs to the 1950s and 1960s ; however, behaviorism goes more back in the history. John B. Watson, 1913 and Ivan Pavlov, 1927 and B.F. Skinner, 1938 are the early researchers who contributed to behaviorism. Behaviorism focuses mainly on external behavior and cast away inner psychological processes. In 1958 methods like "systematic desensitization" was proposed by Wolpe for the management of anxiety. In 1958 Skinner gave concept of behavior management, this open path for behavioral therapy. When this idea got published, the whole world accepted the idea. These theories were the contemporary theories of Cognitive Behavioral Theory.

2.1.2 Cognitive Theory

The CBT has heredity in the Greek history in the period of Seventeenth or eighteenth century. Plato had conceived the idea that the psychology of one's mind i.e. the cognitive state is what one experiences in the actual world. Around this period only other philosophers also supported this idea.

The behavioural therapy as we said earlier totally neglected the inner thinking ways but Albert Bandura in 1969 objected to the long-established belief in his research called the "Principles of behavioural modification." In his work he stressed up on significance of the mental state behind any action of behaviourism. His studies were further supported by Albert Ellis's work naming Rational Emotional Therapy. His work gave birth to this era's cognitive therapy. His work was further elaborated and developed up on by A. Beck in 1970, 1976 and 1995. A Beck is known as the father of Cognitive Behavioural Therapy. A Beck blended the two theories of behaviourism with the cognitive state. Other names who contributed successfully to the CBT were Dobson and Dozois , 2001, Ellis , 1962, Kendall and Hollon , 1979 ,Mahoney,1974 and Meichenbaum, 1977.

2.2 Emotion

Many theories exists about how emotion are caused and how they're expresses, many emotion models exists and used in emotion processing. Darwin, Ekman theory proposed six emotional expression i.e., anger, fear, happiness, surprise, sadness and, disgust. The appraisal theory for the process of emotion experience is most accepted one. According to apraisal theory, cognitive judgment or appraisal of situation is a key factor in the emergence of emotions. According to Orthoney, Clore, and Collins (OCC) [15], following steps are followed when emotions are experienced:

1. An event or action or an object is perceived
2. The event or action is evaluated according to person wish or norms
3. Result of a specific emotion is totally based on perception and evaluation

Now days psychologist present emotions as continuous one in place of discrete which was used in early days, so emotions are demonstrated in n-dimensional space. Now days 2-D valence/arousal plot is adopted. In this plot valence ranges from unpleasant to pleasant and it means personal judgment about negative or positive. While arousal means expressing one's degree of excitation and this spans from calm, medium aroused and activated.

2.2.1 Emotional Brain

The quest for emotional centers in brain has been for years. Neuro-scientists and researchers did thousands of experiment to locate the emotional centers in the brain. Affective neuroscience uses physiological signals, functional imaging, human and animal behavioral experiments for the better understanding of emotions at neurobiological and psychological levels. The pioneer work by, William James [16] and, Charles Darwin [17] lead to breakthrough in studying emotions in human brain. This was followed by emotional model of Walter Canon and Philip Bard [18],[19],[20],[21], James Papez [22] and, Paul MacLean [23]. In the end of the 19th century James-Lange proposed a theory. This theory states that emotion is the experience of change in the body. In the 1920s Cannon and Bard [18],[19] challenged this theory, among others because the changes in body are too slow to be responsible for emotions and artificial body changes are insufficient to generate emotions. They state that the brain region that translates stimuli into emotions is hypothalamus.

Some years later, Papez [22] augmented this idea and made a nice scheme of how emotion would be processed in the brain. It consists of two streams, the stream of feeling and the stream of thinking. He claimed that emotional experiences are a function of activity of both streams, that is computed in the cingulate cortex. Many of this theory, especially the pathways he proposed, are proven to exist, although not all the regions he mentioned are important in emotion processing.

In 1949, Maclean [23] introduced another, more accurate model, and invented the term limbic system. He claimed (as a neo-Jamesian) that perception of the world, combined with information on body changes generates emotional experience, and this integration of knowledge occurs in the limbic system. This theory of the limbic system has been the dominant theory for a long time, although it is now thought that some structures of the limbic system play a less important role, and some other structures play a more important role in the *emotional brain.* Some of these structures are:

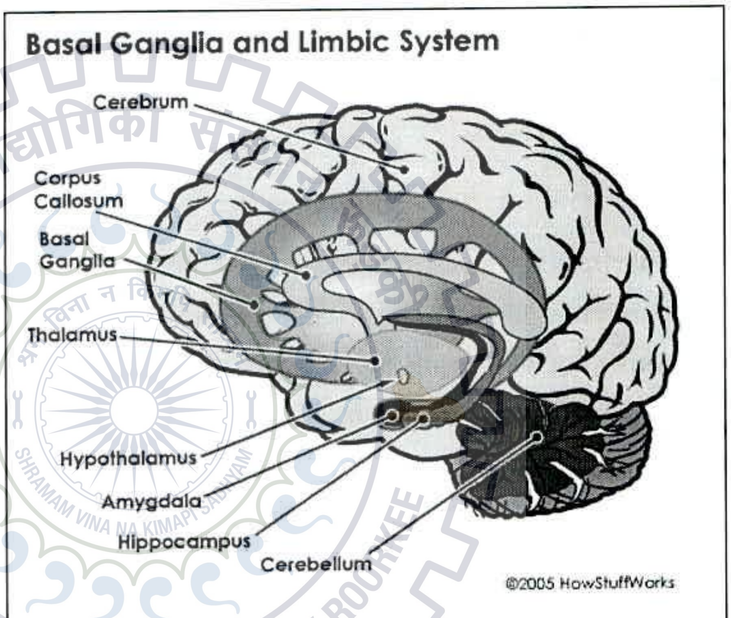


Figure 2.1: The Human Brain

Amygdala performs primary role in the processing of memory and emotional reactions, and its is considered as part of the limbic system. The amygdalae are two groups of neurons deep inside the human brain. Together, they are considered as the most important center for emotion in the brain. Together they are called the amygdala. One of its functions is to interpret the emotional value of incoming signals. When a person receives some sort of signal with some emotional load, it is recognized by the amygdala. Another function of this organ is fear conditioning: it helps in learning a connection between some stimulus and a threatening event. For example, when a rat hears a sound and gets an electric shock, he will connect these two things after a number of combinations. Afterwards, he will become afraid of the sound. A third important function of the amygdala is the consolidation of long-term emotional memories.

Prefrontal Cortex Just as the amygdala, the prefrontal cortex (PFC) plays a role in reward processing. Neurons present in the PFC region can usually detect the changes in reward value during learned stimuli [25]. 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'.

Anterior Cingulate Cortex This part of the brain is generally subdivided into a `cognitive' and a `affective' part. The affective part is suggested to monitor disagreement between the functional state of the organism and any new information, which might have affective consequences [24].

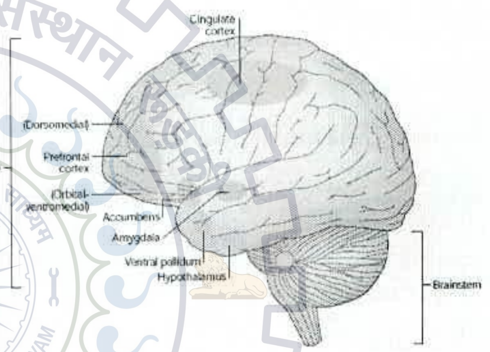


Figure 2.2: Key structure within a generalized emotional brain

Hypothalamus The hypothalamus is the part of the brain that controls many processes in the body, such as body temperature, hunger and thirst. It also handles the release of some hormones. As such, the hypothalamus is involved in processing emotions and sexual arousal.

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.

2.2.2 Models of Emotions

Emotion is a phenomenon which is difficult to measure on some measuring scales. However, major advances are seen in recent years to measure components such as mechanism in the brain, appraisal, expressive behavior and, physiological response pattern individually. Both nonverbal (face texture and speech expression) and physiological signals can be used to infer human emotions.

Psychologist use following two methods to study the emotional state of human:

(a) discrete emotion approach and

(b) dimensional approach.

Discrete Emotion Approach dates back when languages were discovered and words were formulated to describe one's emotions and feeling to others. Darwin made it acceptable to biological and sociological society. Discrete emotion theory assumes that there are seven to ten core emotions and thousands of emotion words which are all synonyms these core emotions [Wikipedia]. The most well known *core emotions are: anger, fear, sadness, happiness, disgust, surprise, content and, fear.*

Dimensional Emotion Approach was pioneered by Wilhelm Wundt who attempted to develop a structural description of subjective feeling as it is accessible through introspection. He suggested that these subjective feelings can be described by their position in a three-dimensional space formed by the dimensions of *valence (positive–negative), arousal (calm–excited), and tension (tense–relaxed)*. Wundt believed that the mental phenomenon of feeling, as described by these three dimensions, covaried with measurable states of the body such as, for example, physiological arousal. Many modern theorists limited themselves to 2-dimensional approach that is valence arousal plot, because it is difficult to identify the third dimension (tense-relaxed).

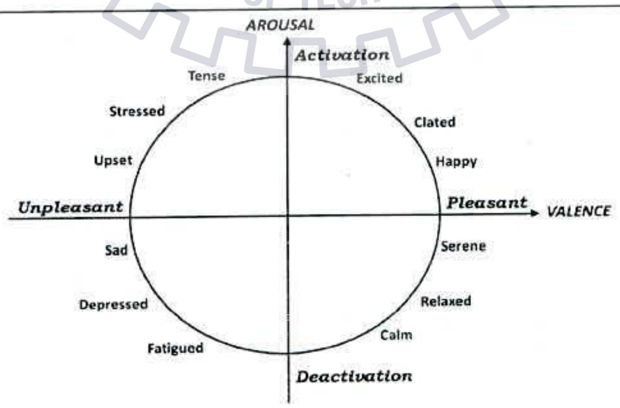


Figure 2.3: Different emotions on Valence-Arousal plot

Model used in our project

Most literature on emotion uses valence-arousal dimensional approach, because of two reasons: simplicity and universality. This make using the model easily and results can be compared with other literature. Basic emotion approach is difficult to use since it is having only few core emotions in discrete manner. For this reason we use dimension approach for our project.

2.3 Aim of Dissertation

The main objective of the dissertation work is:

1. Sort few videos out of million available online, which are able to elicit particular emotions in subjects. Cut short videos to make them of 120 seconds approximately.
2. To record various physiological electrical signals, EEG along the skull and ECG of the subject during watching videos.
3. To study the changes occurring in different parameters of EEG and how this can be detected using signal processing techniques.
4. To find out the location of activity, when emotions were elicited.
5. To study the changes occurring in various EEG parameters when emotional stimuli intensity is increased

2.4 Layout of Dissertation

The following chapters cover the whole dissertation work; introduction to each chapter is given:

(a) Chapter 1 provides an introduction to emotions and how emotions recognition can change the world of computer. The emotion recognition can prove a great boom in the field of BCI and HCI

(b) Chapter 2 gives a brief description about cognitive behavior therapy, emotions, how emotions are perceived in brain and, what are the different models of emotion, which model is best and which used in this work. And provide brief outline of the dissertation.

(c) Chapter 3 gives a brief description about the technologies available for recording emotions. What are the different available technologies, which is best and which one is used in this work.

(d) Chapter 4 gives a detailed description of the methods and methodology used in this work. It also provides the details of the experimental protocol followed and the experimental setup.

(e) In chapter 5, experimental results are discussed in details. It provides the changes occurring in different parameters of the EEG and ECG signals.

(f) Chapter 6 is all about conclusion of the whole work.

CHAPTER 3

STATE OF ART TECHNOLOGIES FOR RECORDING EMOTION

There are so many technologies present in today's world to study the emotions or to make emotion intelligent system. Emotions can be recognized using facial expressions, vocal expressions and physiological electrical signals. Here we are going to discuss the emotion recognition using physiological signals. For studying emotion from brain activity and heart activity, we need information on how brain measures emotion. How heart rate is affected by the emotion perception. We need information how to measure brain activity and heart activity. Several methods on measuring brain activity and, heart activity are discussed in next section. The major modalities used for emotion recognition are listed below:

1. Electroencephalography (EEG)
2. Heart rate variability (HRV)
3. Functional magnetic resonance imaging (fMRI)
4. Positron emission tomography (PET)
5. Electrooculography (EOG)
6. Electromyography (EMG)
7. Electrodermal activity (EDA)

3.1 Electroencephalography (EEG)

Electroencephalography (EEG) utilizes the electrical activity generated due to firing of the neurons in the brain. When neurons fire the electrical potential is created. EEG measures the combinational electrical potential of groups of neurons over the skull. Due to presence of skull and, tissues between the firing center and the EEG electrodes, it make difficult to get exact location of the activity.

To measure EEG, a cap carrying array of electrodes is placed on the head. The numbers of electrodes present in the cap are rising day by day with the advancement in technology. The electrodes present in cap are arranged according to international standard 10-20 system, as depicted in the figure. This standard electrode placement makes the results obtained can be easily compared. The brain activity or EEG signals can be divided in following categories. This depends on the frequency bands in which the signal lies.

Rhythmic activity

The firing of brain neurons generates a rhythmic signal which is combination of many signals. These signals can be differentiated in the terms of frequency bands. Below be mentioned few well known frequency bands.

Delta band This band extends upto 4 Hz and having high amplitude. Delta band is mainly associated with deep sleep.

Figure 3.1: Biopac system cap for EEG

Theta band The theta band frequency ranges from 4 Hz to 8 Hz. Mainly observed in young children and associated with drowsiness or meditation.

Alpha band The alpha band frequency ranges from 8 Hz to 12 Hz and popularly known as basic rhythm. It is many associated with closed eye and relax condition.

Beta band The beta band frequency ranges from 12 Hz to 30 Hz and this band is associated with active thinking and active concentration.

Event-related potentials (ERP)

Event-related potentials (ERP) are potentials that occur after some event, most apparently after unpredictable events. This potential occurs in the stream of ongoing brain activity, and most of the time it is difficult to extract some specific activity. If it is known when such an event occurs, it is possible to time-lock the EEG signal, and extract the ERP from the signal. One of the best known ERPs is the P300, which occurs around 300 milliseconds after the event.

Event-related (de-)synchronization

Besides the ERPs, the rhythmic activity of the brain can also be altered by external or internal events. These events can cause an increase or decrease in the power of one of the frequency bands. This change is said to be caused by synchronization or desynchronization of the activity of different neurons, resulting in band power changes.

3.2 Heart Rate Variability (HRV)

The variation in the electric potential signal of heart varies over time and this is depicted in electrocardiogram (ECG) signal. The ECG signal is recorded by using standard 5 lead of Biopac system on the surface of the body. Each ECG beat generally consists of three waves: the T wave, the P wave and, the QRS complex. Since the sympathetic stimulation effects can be seen as the changes on cardiac muscle, the HRV proved to be one of the most important choice for arousal detection using comparison of sympathetic and parasympathetic frequency band of the time series.

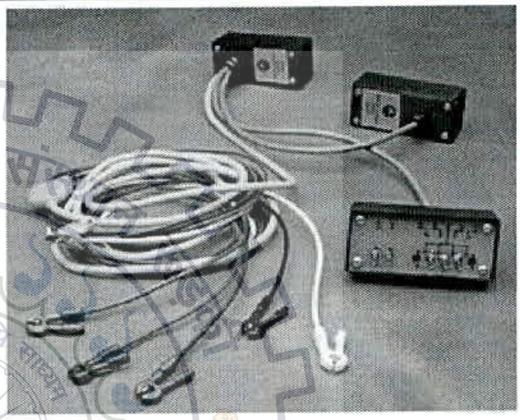


Figure 3.2: Biopac ECG measurement electrodes

3.3 Functional Magnetic Resonance Imaging (fMRI)

Functional magnetic resonance imaging (fMRI) is another method that depends on the blood flow. Active neurons are known to consume oxygen that is carried by hemoglobin.

This consumption of oxygen changes the magnetic properties of hemoglobin, and these magnetic properties are measured by the fMRI

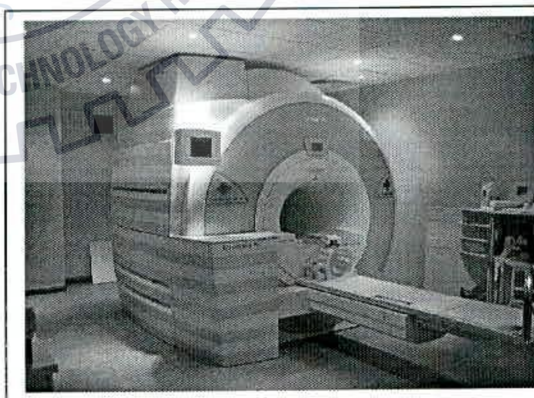


Figure 3.3: An example of fMRI

system. So, indirectly the brain activity is measured. Just as pet, fMRI has a high spatial resolution, but a low temporal resolution. Moreover, the equipment needed is very expensive.

3.4 Positron Emission Tomography (PET)

With positron emission tomography (PET), a radioactive isotope is injected into someone's blood. Because this isotope emits positrons, and is taken with the blood flow, a machine can measure the blood flow. Since it is believed that the blood flow in the brain is highly correlated with brain activity, the machine can show brain activity. Pet is able to measure activity with a high spatial resolution, but it has a low time resolution and a time delay due to the time it takes before the radioactive material has arrived in the brain. Another disadvantage of this method is the radiation a person is subjected to.

3.5 Electrooculography (EOG)

Electrooculography (EOG) is the technique for measuring retina rest potential. In this pair of electrodes is placed above and below eye or on left and right of the eye for measuring eye movement.

3.6 Electromyography (EMG)

The electrical activity produced by the muscle movement can be recorded using Electromyography, when muscles are electrically or neurologically activated. Measured EMG potential varies from 50μV to 20-30mV. Electrical activity produced by muscle movement can be used to detect patterns related to emotion.

3.7 Electrodermal Activity (EDA)

Electrodermal activity is the technique for measurement of skin conductance, which varies with its moisture level. This of interest for emotion recognition because sweat glands are controlled by sympathetic nervous system, which makes it good indicator of stress and anxiety. EDA suffers from latency, with a delay of approximately one second for a response to be evoked, followed by approximately three seconds for the effect to dissipate. It is among the most basic and low cost physiological modalities available, and is widely used in physiological emotion recognition, including video games. EDA is commonly read between two fingers on either hand, although is not limited to this area of the body.

3.8 Modalities Used in This Work and Their Significance

To select few modalities out of so many available is big task. In our work we considered following factors for choosing particular modality:

(a) **Applicability of the modality**: - One of the important criterions, the available modality must be useful and changes can be easily detected.

(b) **Availability of the modality**: - This is again an important criterion, because the work to be executed in departmental lab, so the modality should be easily available. The selected modalities should be cost effective. Biopac machine for EEG and ECG recording is easily available in the Biomedical Instrumentation Lab.

(c) **Universality of the modality**: - The recorded parameters should be such that they can be compared with the results available across the globe.

EEG and ECG are used for this because of reasons listed below:

1. User independent emotion recognition system
2. Emotion influence central nervous system (CNS), using this modalities changes in CNS can be directly recorded

CHAPTER 4

MATERIAL AND METHODOLOGY USED

Measured EEG signals are a valuable source of information about brain activity. However, since brain activity only produces very weak signals, the EEG signals contain a lot of background noise. Before using the signals for emotion recognition, they have to be preprocessed, in order to remove unwanted noise. Although EEG signals contain a lot of information, they also tend to result in very large amounts of data. As mentioned in chapter 2, the information in EEG signals includes information about emotions. Our program has to extract the valuable information from the large amount of data. For this task, we will first reduce the amount of data available. This process is known as feature extraction and extracts specified measures that is useful for our task from the signals. These features should contain enough information about the emotion. After having reduced the size of the data, the emotion has to be recognized from the features. For this purpose several classification methods exist to classify a given EEG signal into a number of emotional classes.

This chapter will provide information about methods to preprocess the measured EEG signals (section 4.1), present preliminary study (section 4.2), presents experimental protocol in (section 4.3) and introduce experimental setup (section 4.4) and feature extraction (section 4.5). Finally the methods for eliciting emotion (section 4.6) and recording EEG data (section 4.7) will be explained.

4.1 Preprocessing of Signals

Preprocessing is a step which involves processing of EEG and ECG signals in such a way that they are ready to used. Recorded EEG signals are combination of required information and, too much amount of noise and, artifacts. The aim here is to remove all the unwanted content in the signal and, filter out noise so that only original brain activity content is available.

4.1.1 Noise and Artifacts

The electrical activity produced by the brain is in the order of microvolts. These signals are very low in amplitude so they contain large amount of noise. static electricity or electromagnetic fields are main source of error, these are produced by surrounding devices. The EEG is highy influenced by the artifacts produced by the body movement. For example, eye blinks or other eye movements produce large spikes in the EEG signal. Other muscle movements also leave their mark in the brain signal. In many studies the participants are asked not to move or to blink as few times as possible. However, in many practical situations this is not feasible.

Filtering

Many noise that is present in the EEG signals can be removed using simple filters. The relevant information in EEG, at least for emotion recognition, is found in the frequencies below 30Hz. Therefore, all noise with higher frequencies can be removed using a low pass filter. For example, noise from the electrical net has a fixed frequency of 50Hz. Bandpass filters can also divide the EEG signals into frequency bands, which can be analyzed separately. Low pass and bandpass filters are implemented by Matlab using FIR filters.

Artifacts

Artifacts are somewhat more difficult to remove, because they are not present all the time, and not always in all electrodes. Another disadvantage of artifacts over other noise is the relative high voltage as compared to the normal EEG signals. However, since artifacts contaminate the signal very much, they are a huge problem when using EEG signals. Fortunately, for the same reason many solutions for the problem have been suggested, ranging from very simple to mathematically complex.

Filtering

A very simple method of removing artifacts is simply using a high pass filter to remove the frequencies below 1 or 2Hz. This method assumes there is not much brain activity with very low frequencies, and that artifacts occur at a lower frequency. A great advantage of this method is that its implementation is very simple and it can be combined with the low pass filtering to remove noise with high frequencies. Unfortunately, the method is not very precise, and might remove some useful information.

Artifact rejection

One method of removing artifacts is the rejection of the data sample. Although this is a valid method of removing artifacts, the problem is that there are often not much samples available. If some of the samples are removed, there are even less samples left, which might decrease the quality of the system. Another problem of rejecting data in online systems, is the possibility of losing some important part of the data, which might not return again.

Artifact subtraction

Another method involves the subtraction of electrooculographic (EOG) signals from the EEG data. EOG measures the eye movement. For each EEG channel, a scale factor is estimated for how much it is involved by eye movements. The EOG signal is scaled with this factor, and subtracted from the EEG signal. The main disadvantage of this method is the fact that the EOG signal contains traces of brain activity, especially from the frontal lobe. This activity is also subtracted from the EEG signals, and some useful information is removed. Adaptive filtering. The use of adaptive filtering in another method for the online removal of EOG artifacts. This algorithm estimates the clean EEG signals by subtracting the filtered EOG signals from the measured EEG signal. The filter is adjusted to the signal automatically, and therefore does not need any calibration or learning steps.

4.2 Pilot Experiment

In the pilot experiment, 12 commercially produced movies were first segmented into their scenes. Scene were divided into 2 minutes long excerpts. From these excerpts 46 emotional video clips containing full or part of movie scene were manually selected. The 46 selected videos were shown to more than 5 participants; each video clip is rated accordingly.

In the preliminary study, the participants were thus asked to self-assess their emotion by reporting the felt arousal (ranging from calm to excited) and valence (ranging from unpleasant to pleasant) on nine point scales. Videos were selected to cover different emotional responses. Two past weather reports were also used as neutral emotion clips.

Ultimately, 10 videos were selected to be shown which were between 90 to 126 seconds long. Here the video clips were kept as short as possible to avoid multiple emotions or habituation to the stimuli while keeping them long enough to observe the effect.

4.3 Setup and Protocol for Experiment

Recording setup consist of EEG and ECG recording hardware and software modules for acquiring physiological signals. Biopac system with active electrodes was used for physiological signal acquisition. Physiological signals such as EEG (10 channels) and ECG were recorded during watching video clips. Subjects were instructed to report the emotions what they felt during watching videos on nine point scale.

Twenty participants from different regions and educational backgrounds participated to volunteer the experiment. 18 participants were male and 2 participants were female out of twenty participants. All participants were healthy and varied from 23 to 27 years in age. The participants were also introduced to the meaning of arousal, valence in self assessment procedure, and to the nature of the video content. Each clip started with 10 seconds countdown clip, to provide time to participants to relax and to rate the video.

4.4 Feature Extraction

Psychological studies regarding the relations between emotions and the brain are uncovering the strong implication of cognitive processes in emotions. As a result, EEG signals carry valuable information about the participants felt emotions.

The average power in different frequency band EEG signals was found to be correlated with emotions. Average power is computed from different bands fast Fourier transform (FFT). The average power of the PSD from theta rhythm (4 Hz to 8 Hz), low alpha rhythm (8 Hz to 10 Hz), high alpha rhythm (10 Hz to 12 Hz), beta rhythm (12 Hz to 30 Hz), and gamma rhythm (30 Hz to 48 Hz) was computed from all the 10 channels and for eleven emotions. The total number of features obtained for a trail from 10 channels is 5x10x11 = 550 features.

4.5 Emotion Elicitation

For studying relationship between EEG, ECG and, emotions database is required. Where we know the emotion of the subject during watching video, emotion is known to us. For this study samples of different emotions are required, thus there is need to elicit emotions in subjects artificially. One of the methods for artificially emotion elicitation is empathy, that is to understand the pain, happiness and other feeling of other while watching them so. In this study videos are used as emotion elicitation agents.

4.5.1 Video Database

Selecting appropriate videos that can be used for emotion elicitation, out of billions of available videos was the hard task. For this, out of billion available videos in database few were selected. Initially forty videos were selected of different emotions with varying time length. People were asked to watch videos and report the felt emotions on 9 point valence-arousal plot. Videos having highest rating for particular emotion were selected. These videos were cropped to the length of 120 seconds, having highest emotional content in it.

The following study was designed to study the electrical activation occurring in the rhythmic bands of electroencephalograph (EEG) during audio-visual stimuli. Audio-visual stimuli consists of 10 videos, two each from different categories, viz. fear, anger, funny, sad and, neutral emotional video clips. The video clips were again divided in two categories one having low intensity of emotion and second having high intensity of emotion. Their affective valence was unpleasant, neutral or pleasant, while affective arousal was calm, neutral or excited.

Twenty right handed participants were made to watch emotional video clips. EEG and ECG were recorded simultaneously while watching video clips for 10 channels and 3 channels respectively. The videos were played in such an order so that video having low emotional intensity content is played first and the one having high intensity emotions are played afterwards. The Gamma, Beta, Alpha, Theta and, low Alpha rhythmic frequency bands were extracted from EEG and the average power was computed using FFT. In ECG, RR intervals were extracted and mean RR interval was computed for HRV analysis.

The videos were arranged in following sequence:

Clip 1: Anger 1

Clip 2: fear 1

Clip 3: funny 1

Clip 4: neutral

Clip 5: sad 1

Clip 6: Anger 2

Clip 7: fear 2

Clip 8: funny 2

Clip 9: neutral 2

Clip 10: sad 2

A ten second count down was inserted between every two videos. This was done to avoid overlapping of emotions and previous clip emotion should not affect the next clip emotion.

4.6 Measuring EEG

We want to create a dataset with EEG signals, for which we know the emotion. To accomplish that goal we also have to do some measurements ourselves. The process of measuring EEG signals is not a very simple task. This section will provide some information on the methods and equipment we used for the EEG measurements.

Electroencephalograph proved to be one of the most important physiological signals for studying emotions and for studying the mental state of mind. The EEG is mostly described in frequency bands and in transient known as ERP. The EEG wave is mostly divided into few bands as mentioned above. The frequency bands describe the mental state of brain or how the brain is feeling at particular instant of time. Table 4.1 mentions all the 6 frequency bands typically used in most of the research. Table lists the location of the rhythms, its frequency band and mental state depicted by the band. [26], [27], [28], [29], [30], [31], [32], [33].

Table 4.1: EEG rhythm frequency bands, mental states and location on the scalp.

Bands normal	**Frequency**	**Location**	**Mental state**
Delta	0.1 to 4 Hz	In adults in frontal lobe, in children posterior lobe; generally have high amplitude	Deep, dreamless sleep
Theta	4 to 8 Hz		Intuitive, creative, imaginary dream
Alpha	8 to 12 Hz	Mostly in posterior lobe	Relaxed but not

			drowsy
Beta	12 to 30 Hz	Low amplitude wave, mostly in frontal portion	Alertness, aggitation
Gamma	30 to 100 Hz	Somatosensory cortex	Higher mental activity, cognitive

The international 10-20 system is widely accepted across the globe and is recommended by the international federation of societies and clinical neurophysiology. In this method whole brain is mapped at a distance of 10% to 20% from each location; this also have advantage of avoiding eyeball movement. Odd numbers of electrodes are present on the left part of the brain and even number of electrodes on right portion of the brain. In our study we have also used the 21 electrode cap for EEG acquisition.

4.7 Methodology of Heart Rate Variability recording

HRV recording is done using biopac modules with five electrodes: chest electrode, right arm and left arm electrodes, right leg and left leg electrodes. For HRV it is important to find out QRS interval. The maxima of the QRS curve are used to identify QRS complex and this point is known as fiducially point of the ECG.

The high pass filter range is selected lower than 2200 Hz for the diagnostic modality or this can add disturbance in finding out QRS complex. Sampling rate can be taken high to avoid error.

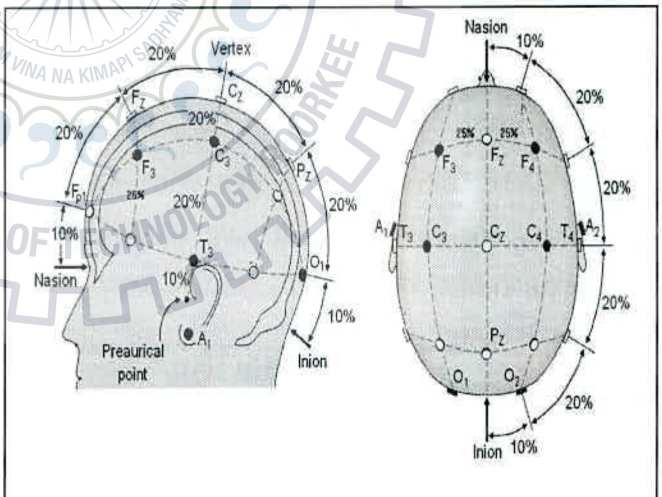


Figure 4.1: The international 10-20 system

4.8 Data Acquisition

MP150 system of biopac is used for acquisition of EEG and ECG in this work. Modules of biopac are used for data acquisition and analysis of data, it's a package with both hardware and software. Analysis of acquired data and its storage is easily possible with this biopac system. This biopac system with acqknowledge software is compatible with windows as well as other operation systems [33], [34].

Table 4.2: Features of biopac MP150 system

Function	**MP150**
Aggregate Sample Rate *Internal MP150 Buffer*	400 kHz
To Cpt. Memory or Disk	300 kHz
Internal Buffer Size	6 Mbytes
A/D Converter Signal/Noise Ratio	86 dB typical
D/A Resolution	16 bits
D/A Output rate	Independent of A/D rate
Communication to Computer	Ethernet (10 base T, UDP and DLC Type II)

Biopac MP150 system is package of both hardware and software together. MP150 system is accompanied by AcqKnowledge software, in which data can be edited and few different functions can be performed like:

(a) Controlling data acquisition system

(b) Real time calculations

(c) Transforms can be find out even after signal acquisition

(d) Performs many file management commands.

MP150 is considered to be the heart of whole biopac system, it acquires data and convert the analog data into digital one and display on the computer. This system is connected using

Ethernet cable. External devices can also be connected to this system using Universal Interface Module (UIM100C) which is provided with the system.

The MP150 system used in this work supports EEG and ECG modules (10 modules for EEG and 3 modules for ECG). The GUI of the MP150 system is shown in figure 4.3.

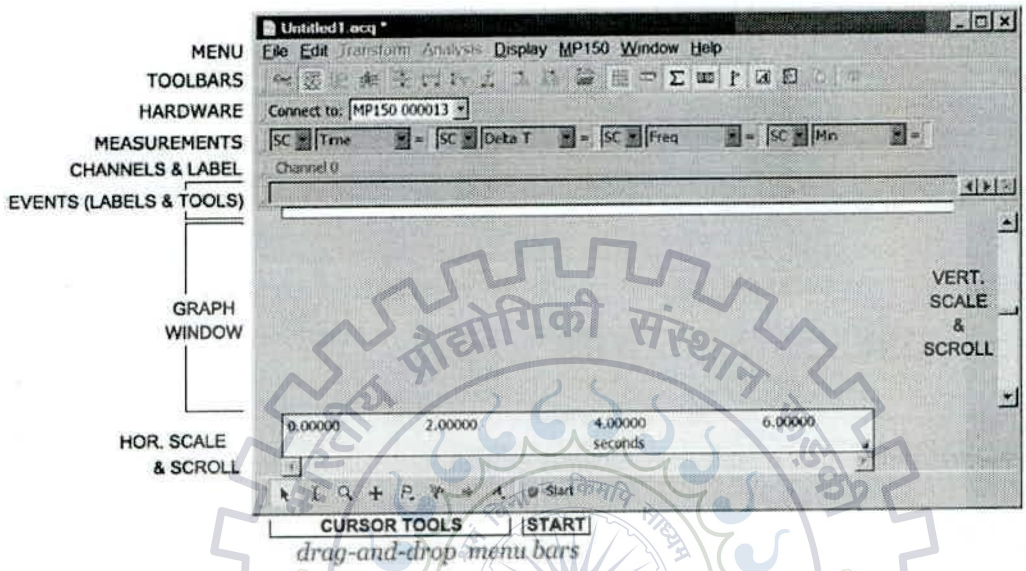


Fig 4.3 GUI of Acqknowledge 4.0 software

4.9 ECG Recording (For HRV)

The following are the steps for ECG recording

Step 1

(a) Connecting the Ethernet cable to computer and MP150 system

(b) Open Acqknowledge software

(c) Select the hardware (MP150 system)

Step 2

(a) ECG module have five electrodes, that are to be connected to right and left arm, left and right leg and, to the chest

(b) ECG module and MP150 system to be connected using communication bus

(c) Channels to be setup using menu bar

(d) For ECG analog channel to be selected

(e) New to be selected from menu bar

(f) Start button and stop button is used for acquiring the ECG signals

(g) Data is stored in default .acq format

If acquired data already exists in the hard drive use: File>**open.** As shown in Fig 4.4

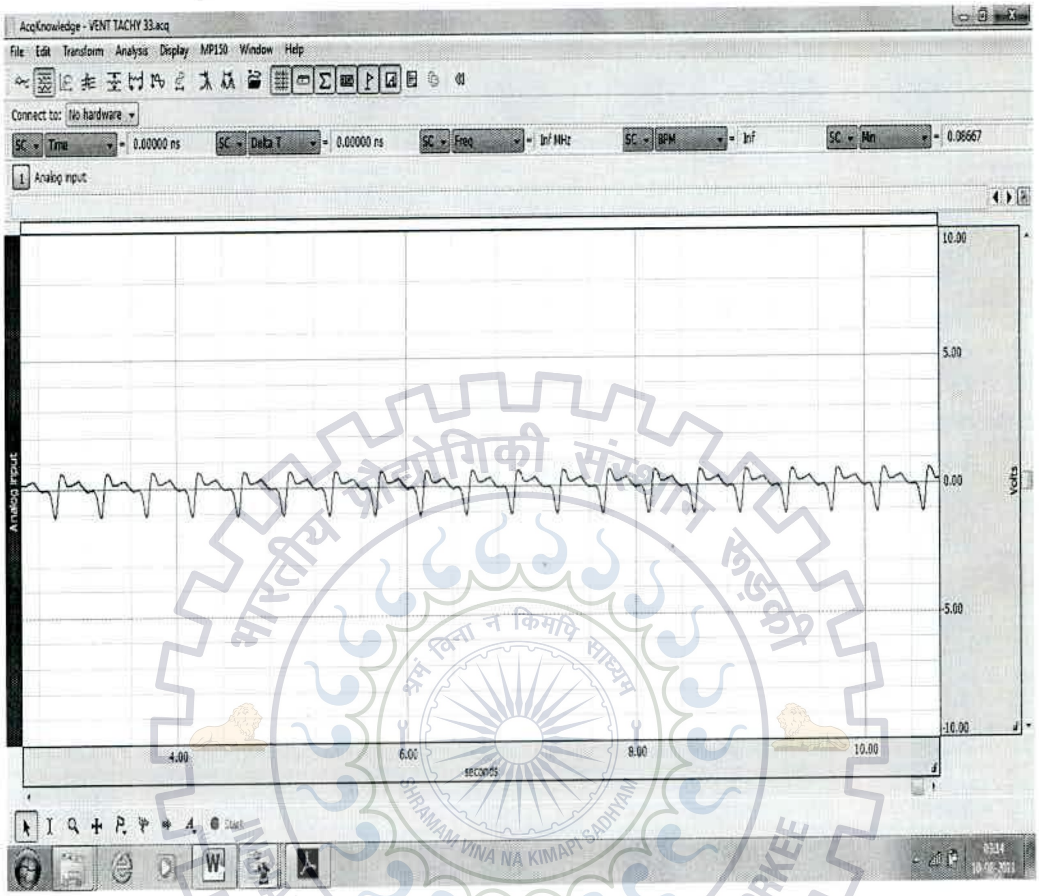


Fig 4.4:- Single channel ECG

4.10 EEG recording

Biopac MP 150 available in the lab is compatible for maximum 10 modules for recording EEG. In this work we have used 10 system modules with a cap having 21 electrodes. [33], [34]. The cap covers the whole skull and thus the brain. The position of electrodes over the scalp and the brain lobes covered by then are listed as:

Table 4.3: Position and electrodes of EEG

POSITION	ELECTRODES
FRONTAL	FP_1,FP_2,F_3,F_4,F_7,F8 &F_Z

CENTRAL	C_3,C_4 & C_Z
TEMPORAL	T_3 ,T_4,T_5 T_6
OCCIPITAL	O_1,O_2
PARIETAL	P_3, P_4,,P_Z

The cap mounted with tin electrodes was placed over the subjects head. The connections were made to MP150 system using communication bus. This connection bus was having different colored electrodes, below the electrodes color representing particular channel and location is listed:

Table 4.4: Channel number and location of electrodes

COLOUR	**CHANNEL**	**LOCATION**
Brown	CH-1	Fp1-Fp2
Red	CH-2	F3-F4
Orange	CH-3	C3-C4
Yellow	CH-4	P3-P4
Green	CH-5	O1-O2
Blue	CH-6	F7-F8
Indigo	CH-7	T3-T4
Grey	CH-8	T5-T6
White	CH-9	Gnd-Cz
Black	CH-10	Fz-Pz

Following procedure was utilized for EEG acquisition:

Step 1

(a) Connect the Ethernet cable to between computer and MP150 system

(b) Open Acqknowledge software

(c) Select the hardware (MP150 system)

Step 2

(a) Subject asked to wear the electrode cap

(b) 10 EEG modules are connected to MP150 system

(c) Channels are to be setup using menu bar (10 channels to be selected for EEG)

(d) For EEG acquisition select analog channel

(e) New to be slected from the menu bar

(f) Start button and stop button is used for starting and ending the process

(g) Check the waveform, if not good, adjust the cap

(h) Data is saved in default .acq format

Step 3

(a) From analysis menu, select electroencephalograph

(b) Select the frequency of particular band required

(c) Select the portion of waveform for which frequency bands are required

Initially a pilot experiment was conducted in *Biomedical Instrumentation lab at IIT Roorkee*. In this experiment, EEG and ECG features were extracted. On the basis of that it was concluded that artificially elicited emotion affects EEG as well as ECG parameters. In this experiment the length of video clips were more than 300 sec, and totally five clips were included. Subjects complained restlessness and, too much muscle movement were shown. Due to this more noise was reported in the signals. Thus, the clip sizes were kept from 70 to 120 sec so as to avoid this noise and artifacts.

CHAPTER 5

EXPERIMENTAL RESULTS & DISCUSSION

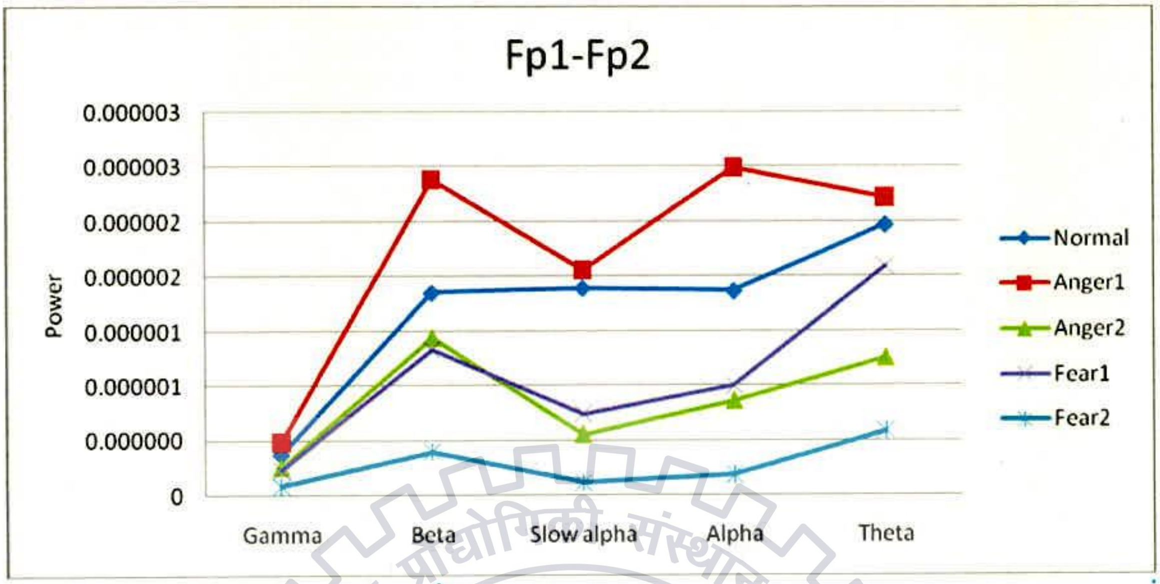
Till now large amount of data is recorded and this data contains good amount of information. Lots of parameters are extracted from the data to convert this raw data into useful information. From these parameters we will see how the different parameters like alpha, beta, theta, gamma and slow alpha varies at different location on the scalp. How the different emotion causes the changes in parameters and what pattern is followed. The physiological parameters were recorded as planned in chapter 3. In this chapter we presented the analysis of physiological signals like EEG and HRV and also determine correlation between the analysis.

5.1 EEG Analysis

The EEG was recorded first for 180 second in relax and eyes closed condition. Then recording is done when subject was watching short movie clips, continuously using a cap with International 10-20 System having 20 electrodes. The acquired EEG data is divided in to the various frequency bands as Alpha (8Hz to 12 Hz), Slow Alpha (8 Hz to 10 Hz), Theta (4 Hz to 8 Hz), Beta (12 Hz to 30 Hz), and Gamma (30 to 48 Hz). The EEG signal rhythmic Frequencies are derived by filtering acquired raw EEG data (or signals). The delta band (up to 4 Hz) was omitted because it contain large amount of noise, noise due to eye blink, neck movement and other. Here Gamma band is limited to 48 Hz to avoid interference due to electrical signals which is about 50 Hz. The raw EEG was acquired by using ten channels spread over the entire skull i.e. frontal lobe, parietal lobe, occipital lobe and, temporal lobe. After this the acquired raw EEG is preprocessed and average power of all the five frequency bands is calculated. The standard Deviation of the EEG signal is also calculated over all the 10 channels covers all the locations over the scalp. In this study we are trying to find out the trend followed by these parameters at different location of the brain, when emotions are elicited.

5.2 Trend seen in EEG

The trend has been seen in this study and show in upcoming sections. The trend has been shown in figures below, where power is plotted against EEG rhythms and variation in emotions are seen clearly (Figure 5.1 to Fig 5.10).



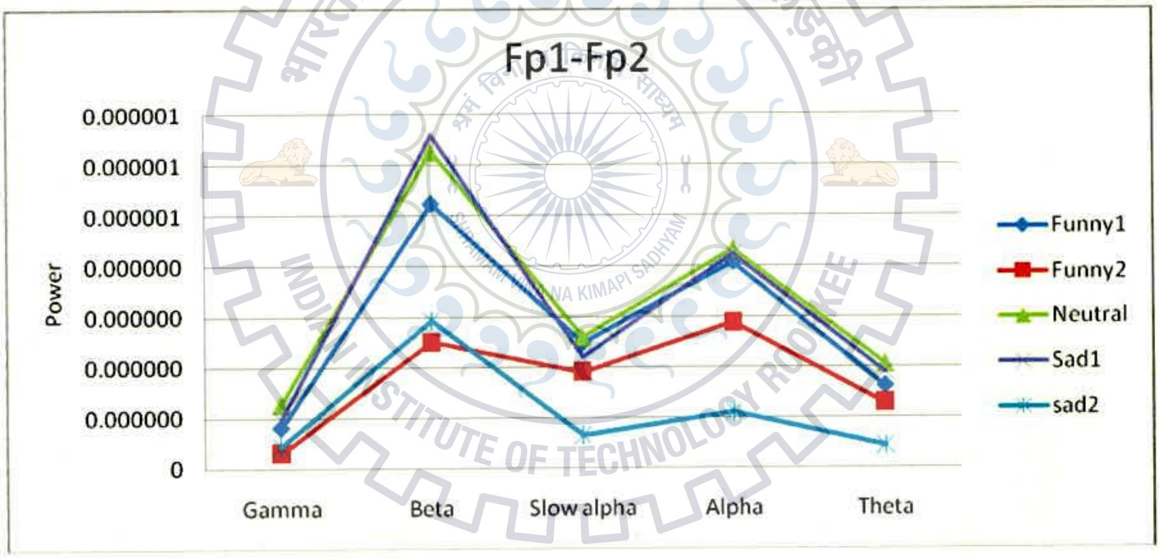
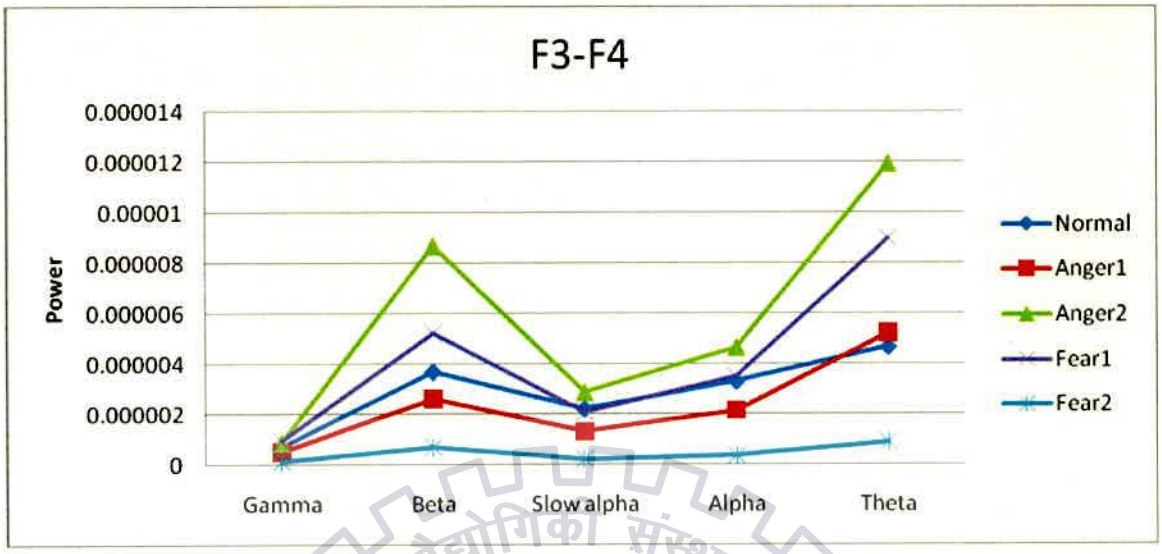


Figure 5.1: Graph of Channel 1 (Fp1-Fp2 region) of EEG, indicating the trends for parameters Gamma, Beta, Slow Alpha, Alpha and, Theta.

In the figure 5.1 the comparison of different emotions are shown with respect to EEG rhythms for prefrontal region of the brain. It is clearly seen that the anger 1 values are higher than normal values and when the anger content is increased (anger 2) the values of alpha, beta, theta, gamma and, slow alpha decreases as compared to anger 1 values. Same trend is seen in fear also. Fear 2 having much higher fear content shows lower parameter values as compared to fear 1. Similar trend is seen for sad emotion. While funny shows reverse trend.



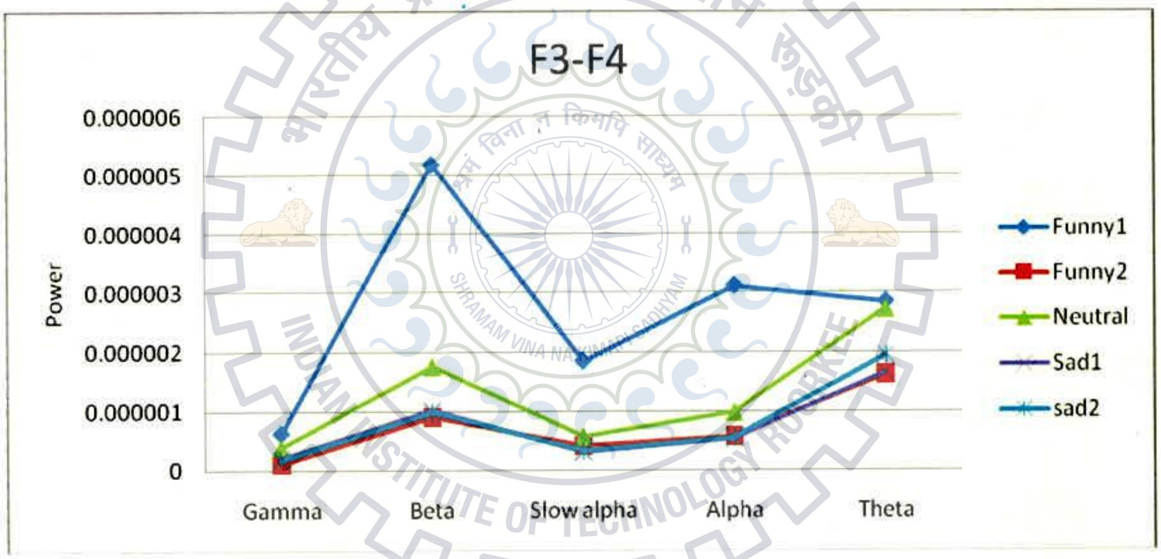
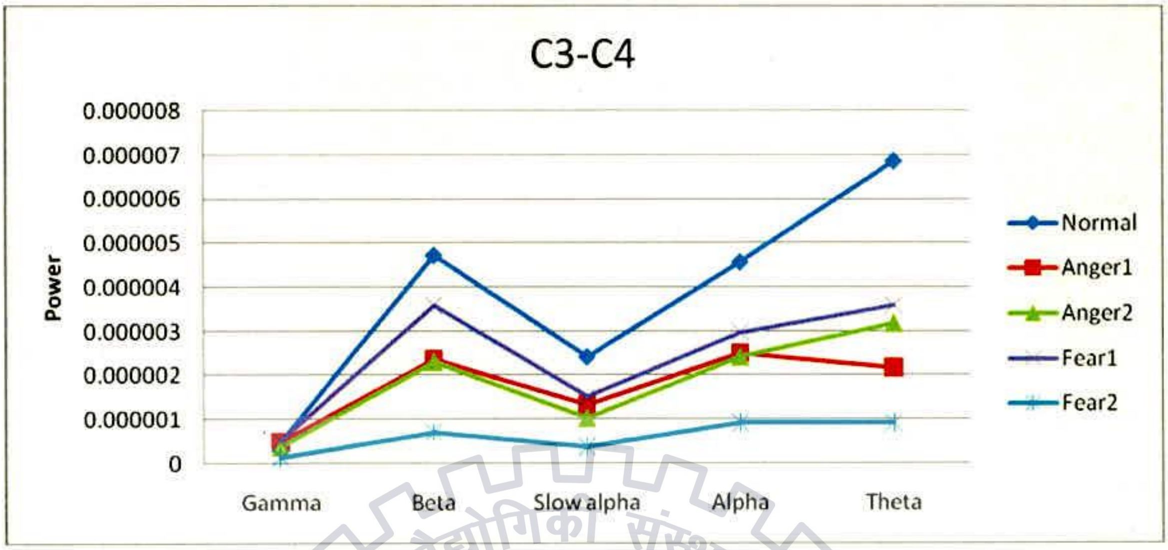


Figure 5.2: Graph of Channel 2 (F3-F4 region) of EEG, indicating the trends for parameters Gamma, Beta, Slow Alpha, Alpha and, Theta.

In the figure 5.2 the comparison of different emotions are shown with respect to EEG rhythms for the frontal region of the brain. Here parameter alpha, beta, theta, gamma and, slow alpha values increases when anger content is increased. While parameter value decreases when fear, funny and sad content increased in the video clips. Thus, we can clearly distinguish the anger emotion in this lobe since it is showing opposite trend as compared to other emotional clips.



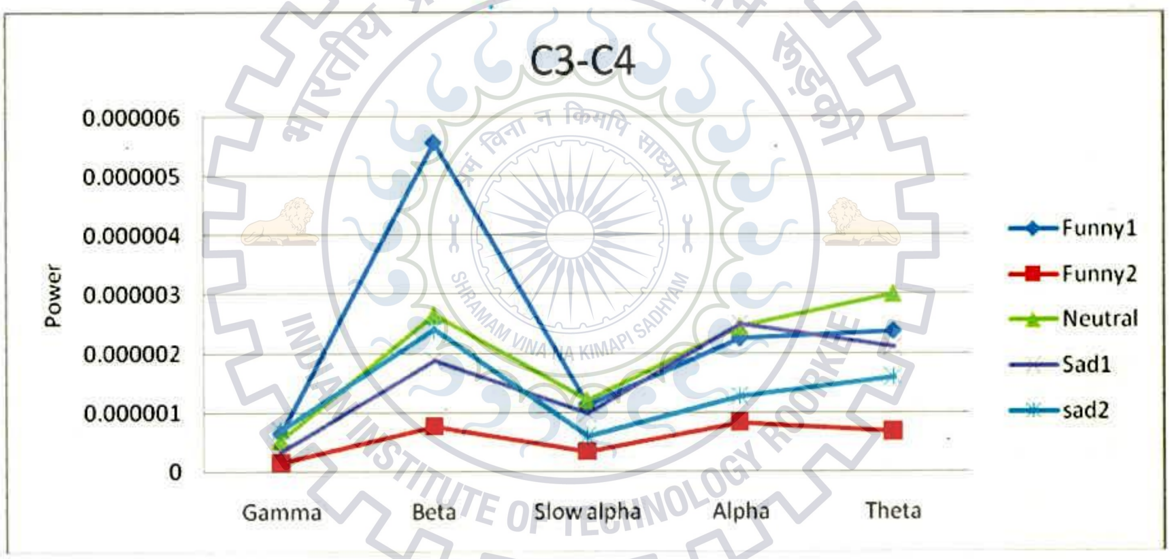
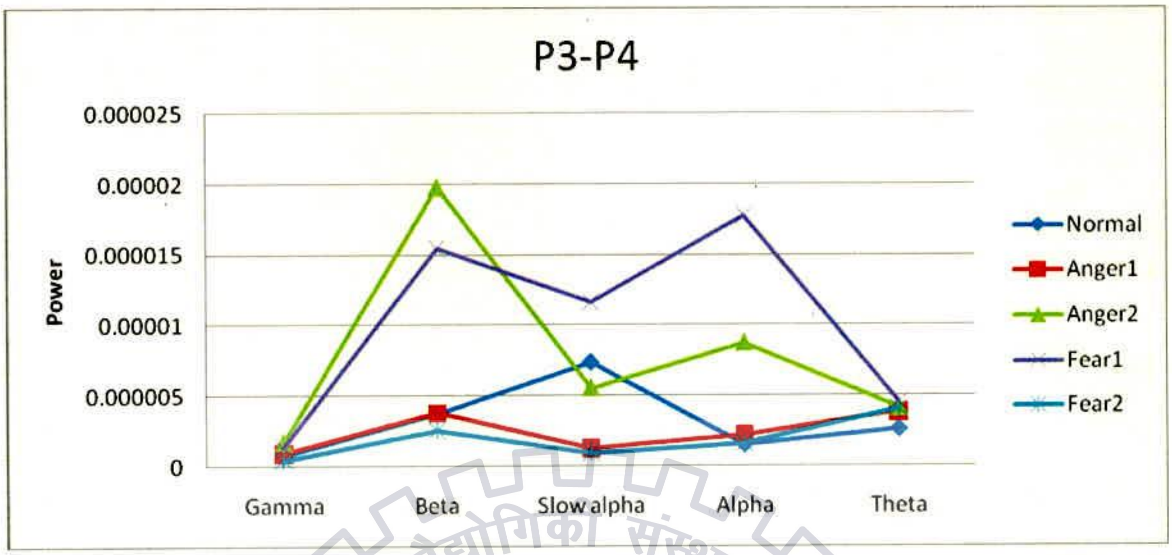


Figure 5.3: Graph of Channel 3 (C3-C4 region) of EEG, indicating the trends for parameters Gamma, Beta, Slow Alpha, Alpha and, Theta.

In figure 5.3 the comparison of different emotions are shown for different EEG rhythm in central region of the brain. We can clearly see that all the emotion show smaller values as compared to normal values. When the emotional content of the video clips is increased, dip in the values of alpha, beta, gamma, theta and, slow alpha is noticed. Except in the theta value of anger, where on increasing anger content increase in theta value is also noticed. And in the gamma and beta values for sad emotion.



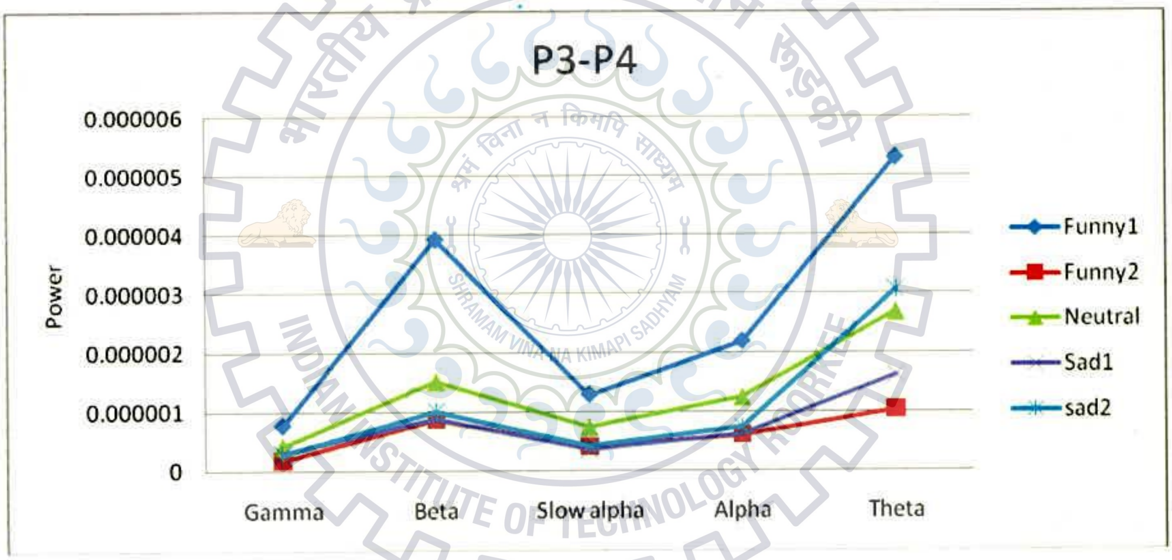
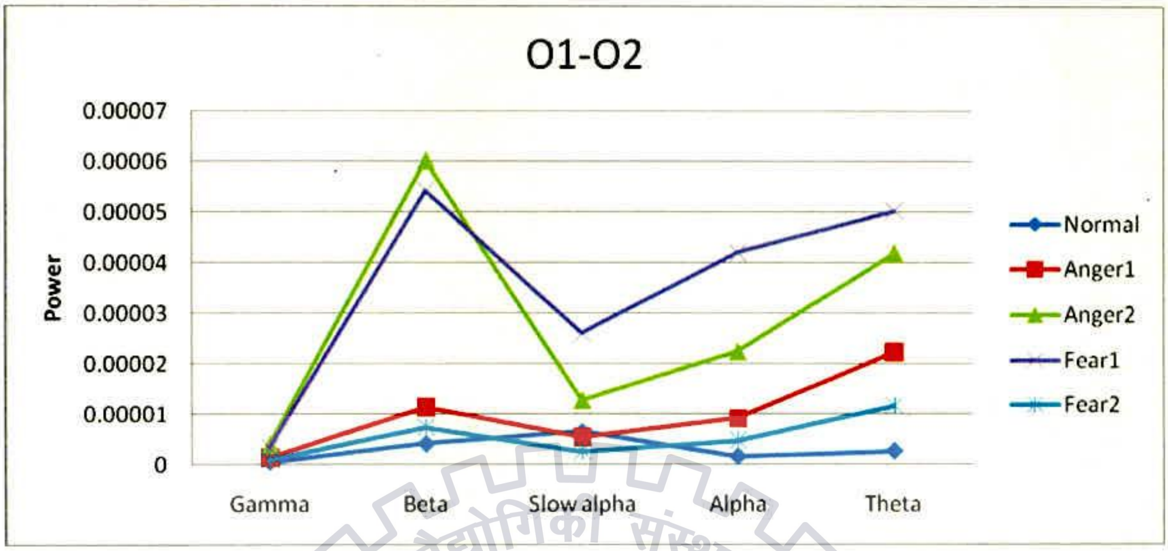


Figure 5.4: Graph of Channel 4 (P3-P4 region) of EEG, indicating the trends for parameters Gamma, Beta, Slow Alpha, Alpha and, Theta.

In figure 5.4 the comparison is shown for different EEG rhythm over the parietal lobe. The Anger and fear show opposite trend in parietal lobe. On increasing the emotion content in the anger clips increase in Gamma, beta, theta, alpha and, slow alpha values is noted. While fear shows opposite trend. On increasing the emotion content in funny videos decrease in alpha, beta, gamma, theta and, slow alpha is noted. While sad shows opposite trend, that is, on increasing emotional content increase in the parameter values is noted.



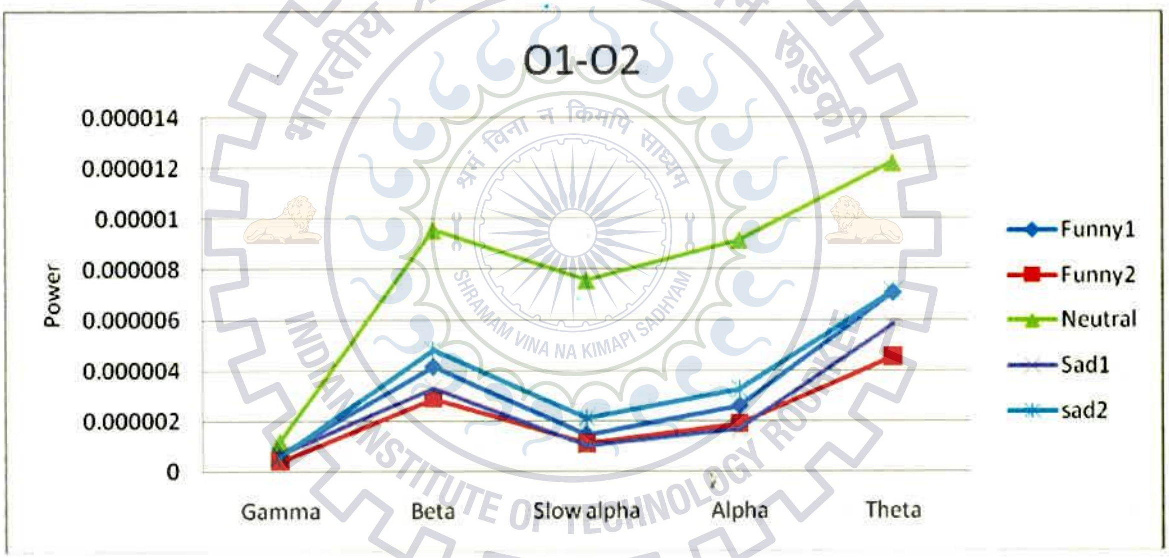
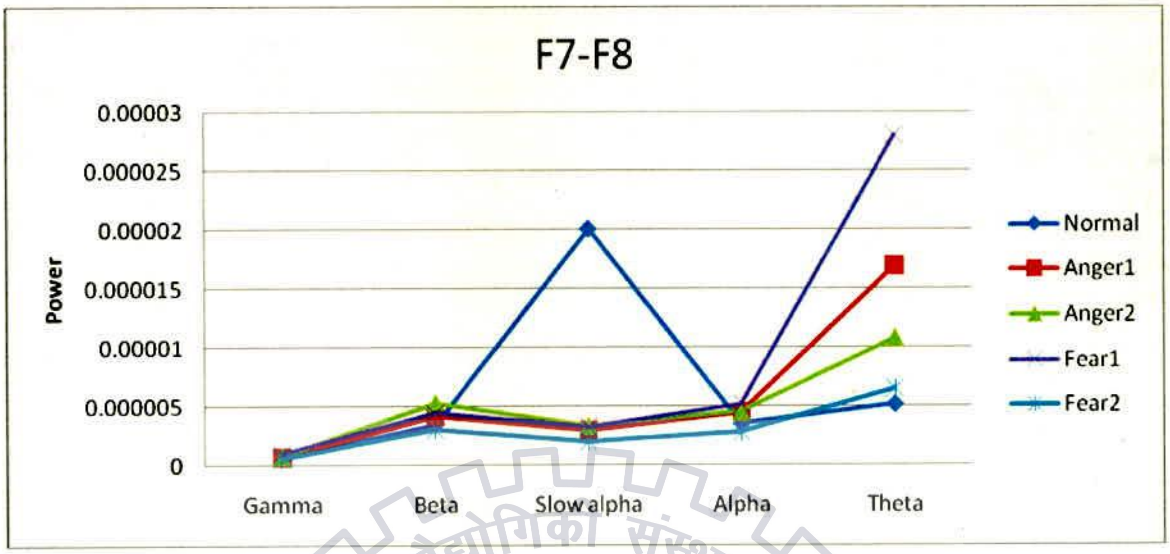


Figure 5.5: Graphs of Channel 5 (O1-O2 region) of EEG, indicating the trends for parameters Gamma, Beta, Slow Alpha, Alpha and, Theta.

From figure 5.5 we note that the values of Anger and fear are greater than normal and, the values of funny and sad is smaller as compared to neutral. In occipital lobe when emotion content is increased the gamma, beta, theta, alpha and slow alpha values increases while in case of fear values decreases. For funny and neutral case, on increasing the emotion content the values of parameter decreases for funny and increases for sad content.



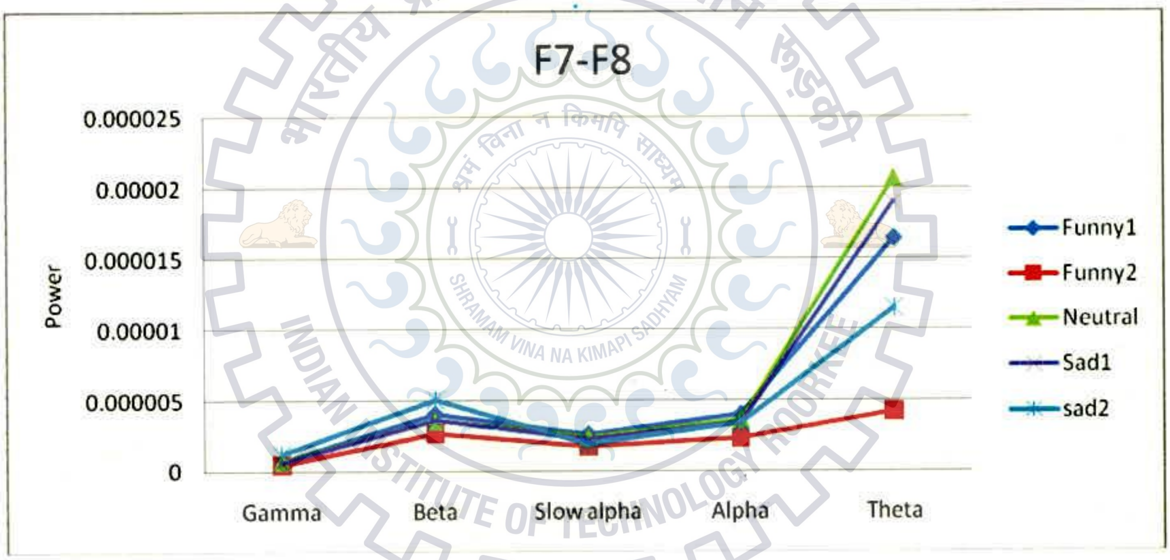
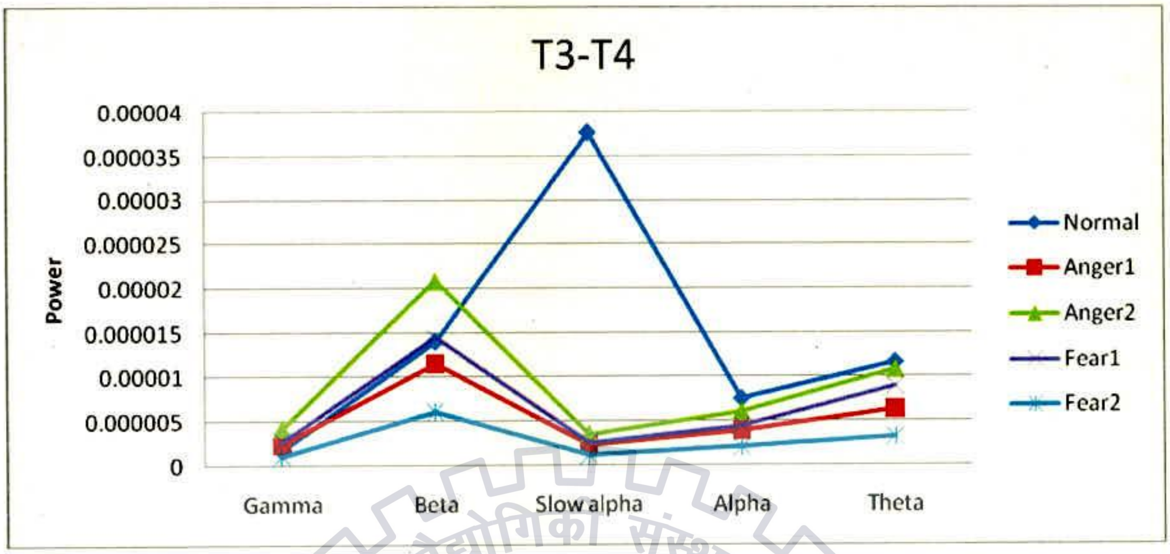


Figure 5.6: Graphs of Channel 6 (F7-F8 region) of EEG, indicating the trends for parameters Gamma, Beta, Slow Alpha, Alpha and, Theta.

From figure 5.6 we note that theta show maximum amplitude as compared to other parameters. Only minute difference is seen in the values of normal, fear, funny, neutral, anger and, sad for gamma, beta, slow alpha, alpha. While large difference is seen in theta values for different emotions.



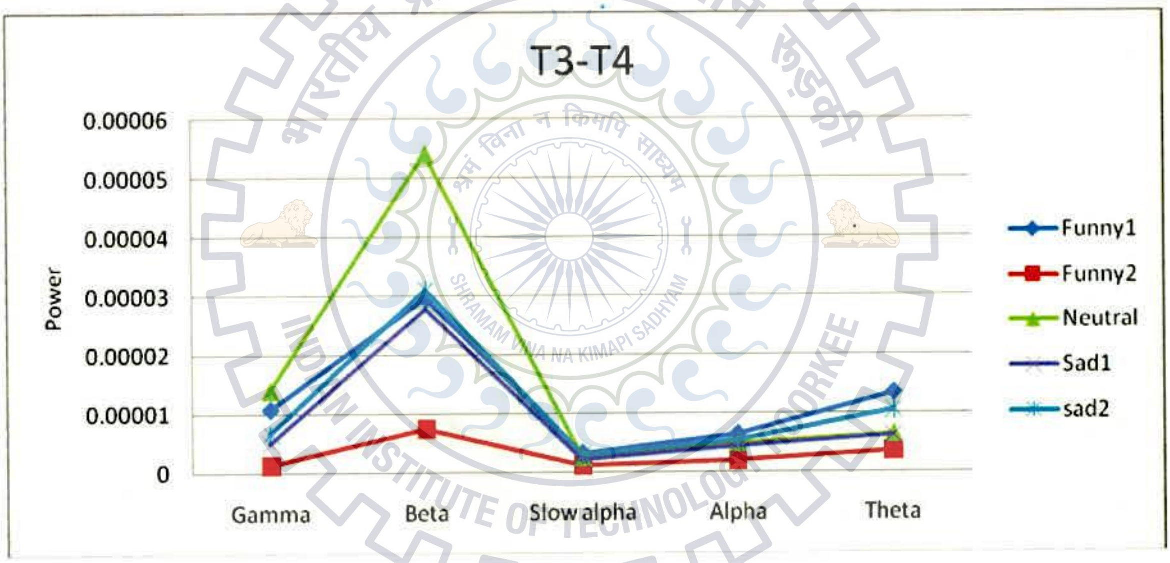
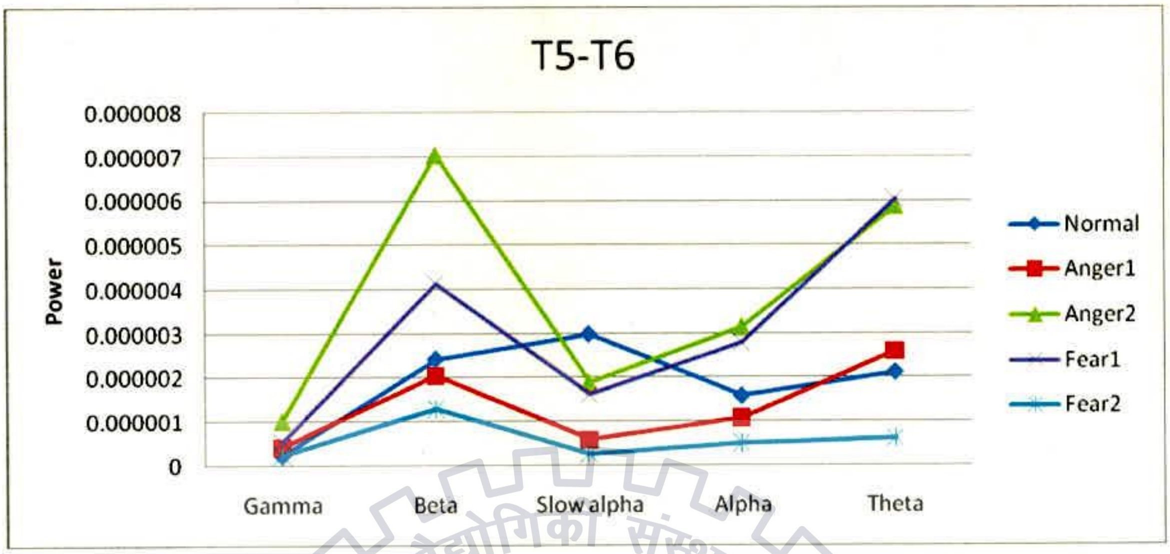


Figure 5.7: Graphs of Channel 7 (T3-T4 region) of EEG, indicating the trends for parameters Gamma, Beta, Slow Alpha, Alpha and, Theta.

From figure 5.7 we note that anger 2 is greater than anger 1 and fear 1 is greater than fear 2. Which show that as the anger content is increased the values of anger increases, while when fear content is increased, the values of all the parameter decreases. Normal show highest value in slow alpha, alpha and theta rhythm. When funny content is increased, value of the parameters decreases.



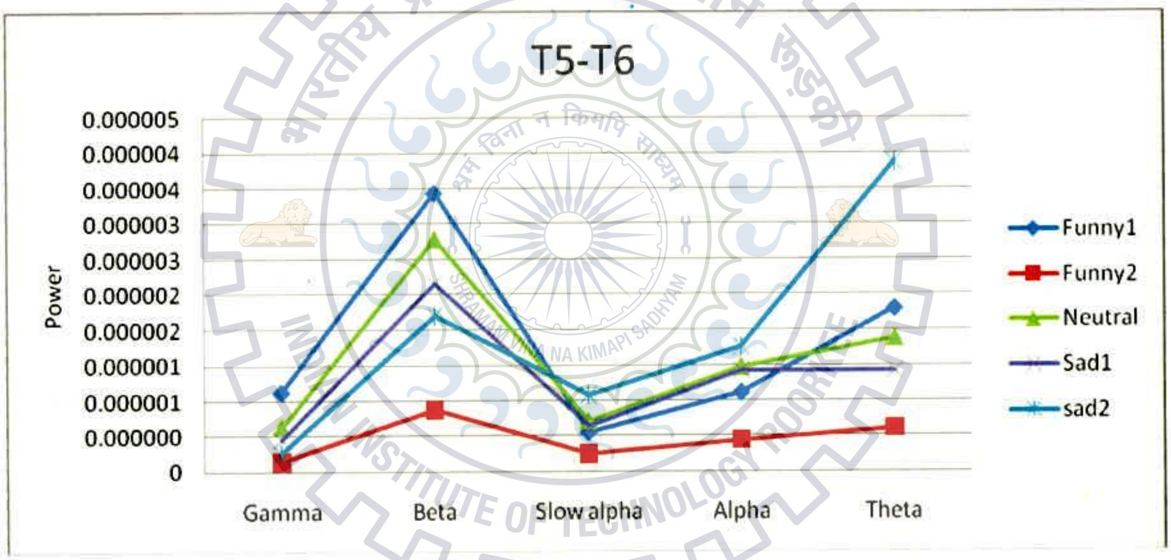
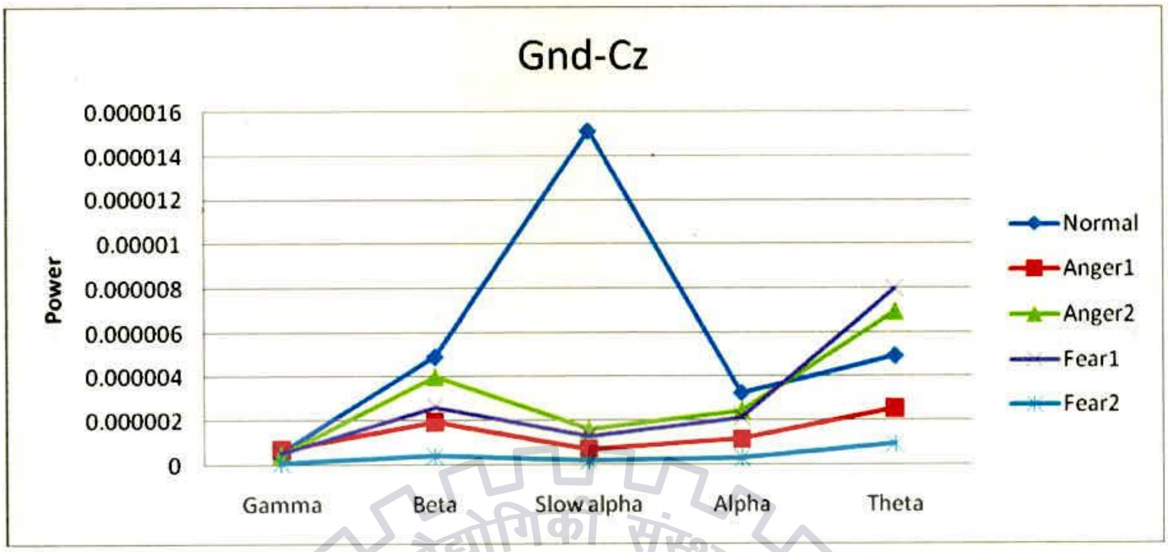


Figure 5.8: Graphs of Channel 8 (T5-T6 region) of EEG, indicating the trends for parameters Gamma, Beta, Slow Alpha, Alpha and, Theta.

From figure 5.8 we note that on increasing the anger content the value of different parameters increases while on increasing fear content the value of different parameter decreases. Normal shows moderate values between anger and fear. When funny content is increased in the videos, the value of parameters decreases. While on increasing the sad content the value of parameter increases except in gamma and beta.



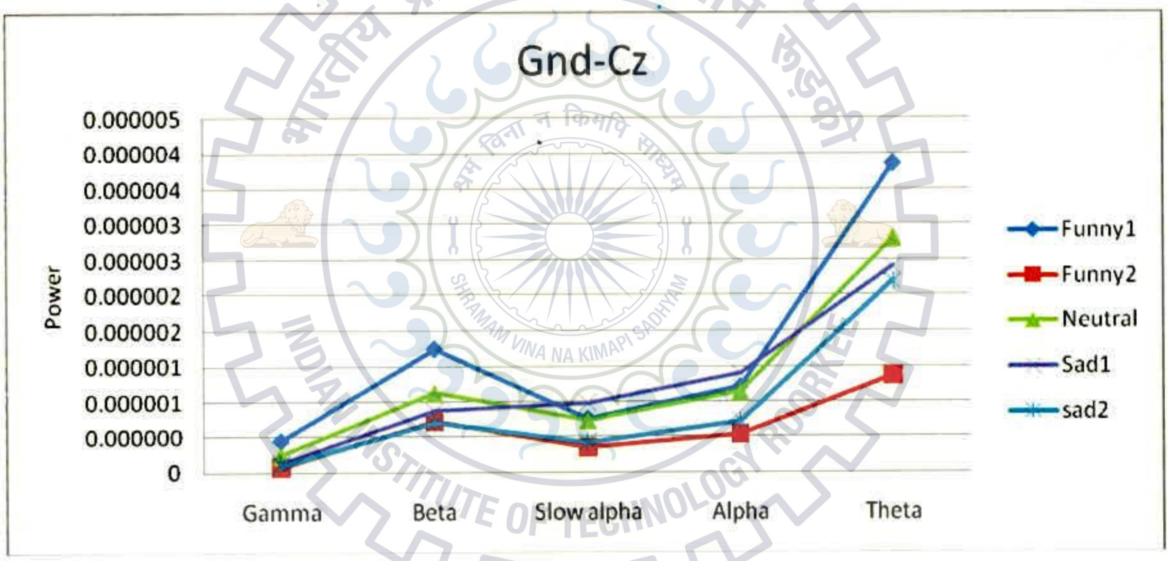
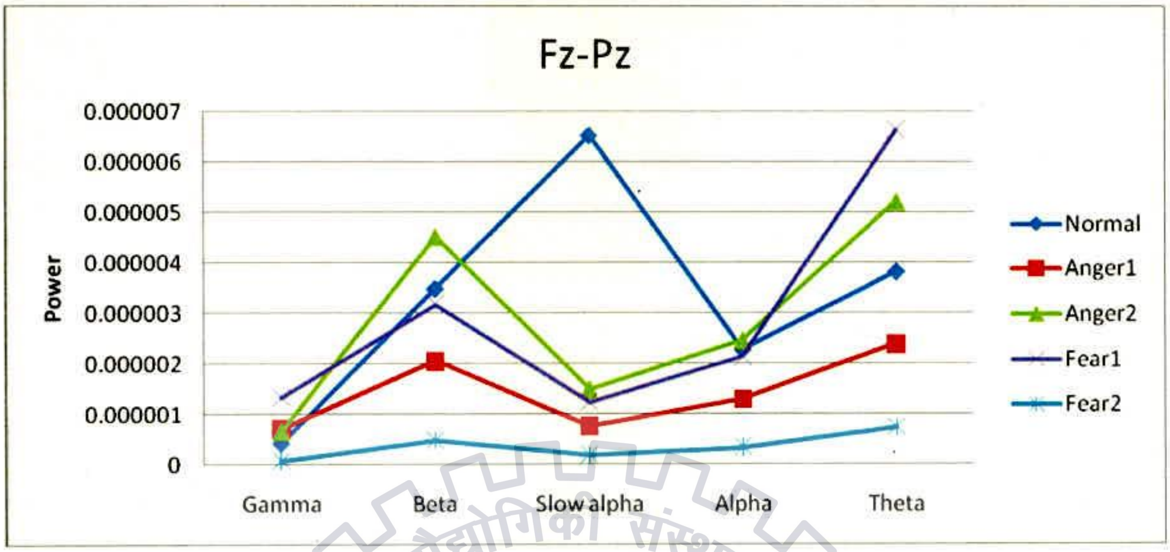


Figure 5.9: Graphs of Channel 9 (Gnd-Cz region) of EEG, indicating the trends for parameters Gamma, Beta, Slow Alpha, Alpha and, Theta.

From figure 5.9 we note that anger value increases on increasing anger content while fear value of different parameter decreases on increasing the fear content in the videos. The value of parameter decreases on increasing funny and sad content in the video. Normal video show highest value for beta, slow alpha and alpha rhythm.



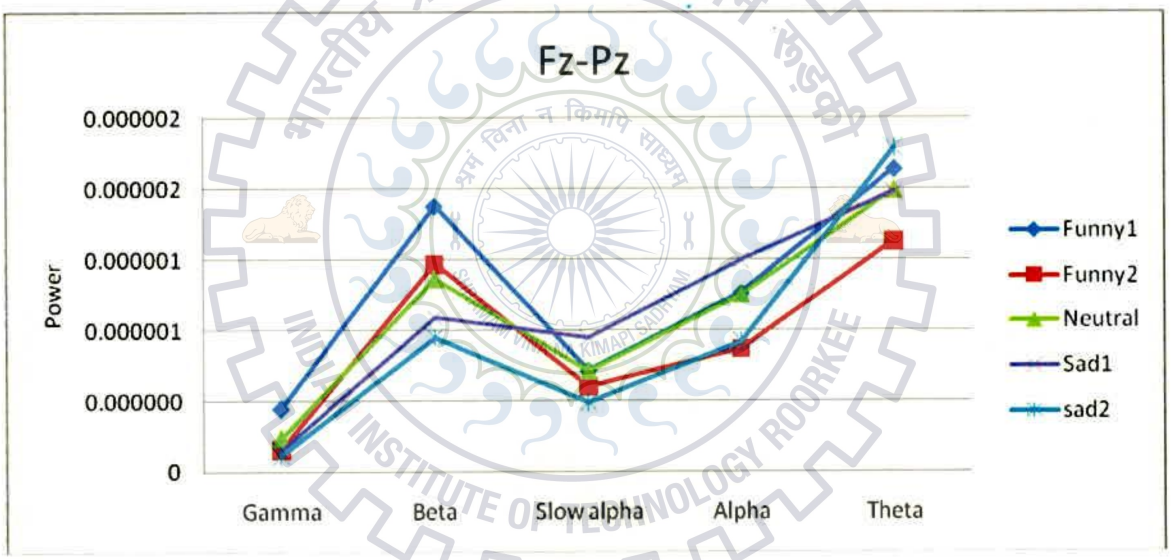


Figure 5.10: Graphs of Channel 10 (Fz-Pz region) of EEG, indicating the trends for parameters Gamma, Beta, Slow Alpha, Alpha and, Theta.

From figure 5.10 we note that on increasing the anger content, the value of parameter increases while on increasing fear content the value of the parameter decreases. Normal show highest value for slow alpha. On increasing funny content the value of different parameters decreases while increasing sad content the value of different parameter decreases except in theta values.

5.3 Analysis with HRV

For HRV analysis the R-R intervals were extracted from the preprocessed ECG signals. For QRS detection modified version of pan-Tompkins is used. For noise and artifacts removal recorded ECG is passed through a high pass and low pass filter. Then a threshold is applied for RR peak detection.

The statistical parameter i.e. mean RR interval is derived from the ECG signal.

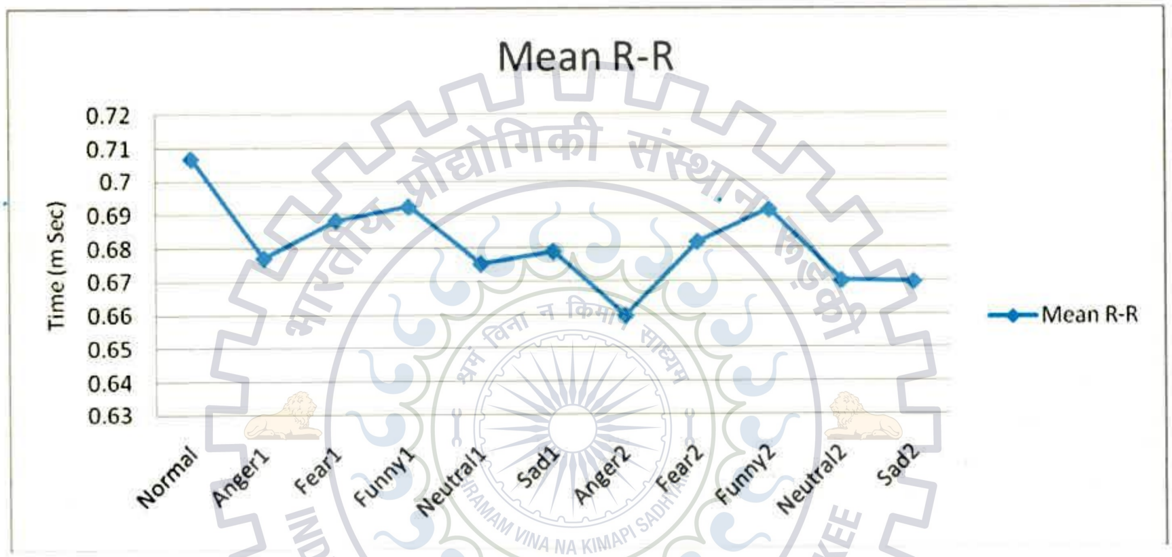


Figure 5.11: Graph of ECG indicating mean RR interval during different emotion elicitation.

From figure 5.11 we note that in the normal case in relax condition RR interval shows highest value. As the subject go through emotional video clips, the heart rate start varying and this variation depends on the content of the video. In HRV analysis it is revealed that the RR interval decreases when a subject go through any emotion as compared to normal conditions. The anger video stimuli shows lowest RR interval and fear emotions show highest RR interval values, within emotion subset. On comparing the values, we see that the RR interval value is less in more emotional intensity videos as compared to its value in less intensity videos. The RR interval for neutral videos is slightly lower that of sad videos. On arranging the RR interval in ascending order, it is seen that anger show lowest value, than sad emotions, than fear emotions and, funny shows highest RR value.

CHAPTER 6

CONCLUSION

The focus of the study during this thesis project was to study how the different parameters of EEG and ECG changes during various emotion elicitation. We have studied human brain and its correlation with emotions, how emotions are perceived in human brain, what are the locations of high activation in chapter 2. Electroencephalograph (EEG) is one of the practical, cheap and easy to use modalities to study brain practically. In many researches it is shown that emotion can be studied using EEG. In affective research emotions are studied in two dimensions viz. arousal ranges from calm to excite while other one, valence ranges from unpleasant to pleasant. The EEG is one which can easily provide information about both the dimensions.

After recording EEG and ECG for all the subjects in chapter 4, we tried different methods for computing parameters. Different methods for feature extraction and signal processing are discussed in chapter 4. We have introduced a method for emotion elicitation using short video clips in chapter 4. Practical information about the emotions is recorded in EEG. In our thesis project we used these methods. A program was built in Matlab to preprocess the raw signals and filter EEG and ECG and extract features from them. We created database of EEG and ECG during emotion elicitation.

During this thesis work many subjects EEG and ECG were recorded during emotion stimuli. While studying the trend followed by different parameters of EEG and HRV we came to know that different emotions affects differently on different location on the brain. In prefrontal region that is Fp1-Fp2, when emotional intensity is increased in the video clip all the emotions shows same pattern. On increasing emotion or anger intensity in the video, the average power of all the parameters i.e. Alpha, Beta, Gamma, Theta and Slow Alpha rhythm decreases. Same trend is seen for fear, sad and, funny videos. Their average power also decreases on increasing the intensity of emotion in the video. For frontal region (F3-F4), when emotional intensity is increased in the video clip anger shows deviation from other emotional videos. On increasing the emotional intensity in the anger video increase in average power of all the parameters is seen.

However, fear, sad and, funny video clips show different trend i.e. on increasing the emotional intensity decrease in the average power in all the rhythmic frequency is noted. In central region, on increasing the emotional intensity in the video clips decreases the average power of all the rhythmic frequency bands is seen. However, the average power of theta rhythm in anger video increases on increasing the emotional intensity. In parietal and occipital region, all the emotional stimuli shows same trend for all the rhythms except anger content. On increasing the anger intensity in the videos, there is increase in the average power of alpha, beta, theta, gamma and slow alpha. While fear, funny and sad emotional stimuli shows trend opposite to this

For temporal region i.e. T3-T4 and T5-T6, when emotional intensity is increased in the anger video all the five parameter average power increases same happens when emotional intensity of the sad video stimuli is increased. The fear and funny video stimuli show different trend than this, on increasing the emotional stimuli in the video content of these videos the average power of all the rhythmic band decreases. In midline region, Gnd-Cz and Fz-Cz, on increasing the emotional intensity in the anger shows rise in average power of all the rhythmic band. On increasing emotional stimuli in fear shows decrement in the rhythmic band average power while fear also shows the same trend. For sad video stimuli, when intensity of sad content is increased in the video stimuli, average power of the entire rhythmic band decreases except theta band. The average power of the theta band increases on increasing the emotional intensity in the sad video stimuli.

This thesis presented a study on the variation of different EEG parameters on increasing or decreasing the emotional stimuli intensity. Thus using EEG it is easy to measure the emotional content of the video, such type of studies can also performed to study the emotions of the consumers while purchasing electronics good and two electronics good can be compared on the basis of this. The company then can modify the electronic good accordingly and make it more pleasing and attractive to consumers.

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