“COGNITIVE RECOGNITION BASED ON EEG SIGNAL ANALYSIS”

A DISSERTATION

Submitted in the partial fulfilment of the

Requirements for the award of the degree

Of

MASTER OF TECHNOLOGY

In

ELECTRICAL ENGINEERING

(with specialisation in Instrumentation & signal processing)

By

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DECLARATION

I hereby declare that this report titled "**cognitive recognition based on EEG signal analysis**" is presented on behalf of partial fulfilment for award of degree **Master of technology** in **Electrical Engineering** with specialisation in **Instrumentation & signal processing** under the guidance of **DR R.S. ANAND & DR AMABALIKA SHARMA department of electrical engineering I.I.T. Roorkee**. I have not submitted the matter embodied in this report for the award of any degree or diploma in this institute or any other institute.

Date: 10.06.2019

Place: Roorkee NAMAN ANAND

CERTIFICATION

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

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NAMAN ANAND

Abstract

Cognitive science is the interdisciplinary, scientific study of the mind and its processes. It is used to examine the nature, tasks, functions of cognition . we study intelligence and behaviour, with a focus on how nervous system represents, process, and transform information. Electroencephalography is an electrophysiological monitoring method to record electrical activity of the brain. It is typically non invasive, with the electrodes placed along the scalp. The DEAP(database for emotional analysis using physiological signals) data set give us the stimulus that is needed for the cognitive analysis by studying the emotional trends of a person. Though in DEAP data set many physiological signals are used but we will be keeping our discussion to the EEG signals only. Emotion refers to the changes in the psychological and physical state as a response to internal or external stimulus event, but there is no widespread consensus on the definition of emotion. Not just that, but also there is an overlapping among the concepts of emotion, feeling and mood. In our work we have used the multi fractal detrended fluctuation analysis (MFDFA) on EEG signals that we acquire from DEAP data set. Now we will do further analysis by calculating the features. These features are nothing but the mathematical modalities of our EEG signal that has been generated through 32 channels which is available to us already in the DEAP data set. Once these features are calculated we can get the idea what parameters are obtained for different channel, different frequency and different feature that we select by comparing them to each other.

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Chapter 1: Introduction

1.1. Cognitive science

Cognitive science is the interdisciplinary, scientific study of the mind and its processes. It is used to examine the nature, tasks, functions of cognition .we study intelligence and behaviour, with a focus on how nervous system represents, process, and transform information. Areas which are studied under cognitive sciences are language, perception, memory, attention, reasoning, and emotion; to understand these areas, cognitive scientists borrow from fields such as linguistics, psychology, artificial etc. The analysis of cognitive science spans several levels of organization, from learning and decision to logic and planning, from neural circuitry to modular brain organization. The fundamental concept of cognitive science is that "thinking can best be understood in terms of representation structures in the mind and computational procedures that operate on those structures.

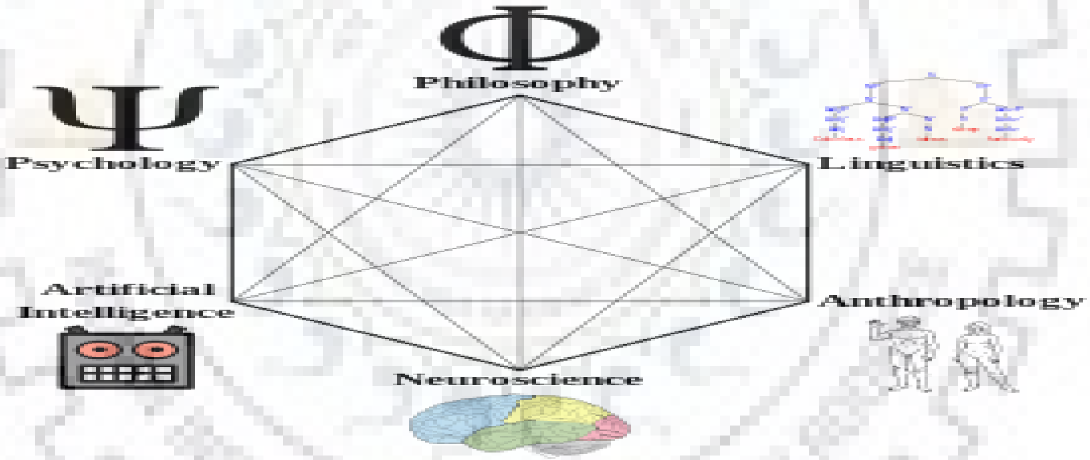


Figure 1.1 : various areas where cognitive science is used.[1]

1.2. Electroencephalogram (EEG)

Electroencephalography is an electrophysiological monitoring method to record electrical activity of the brain. It is typically non invasive, with the electrodes placed along the scalp, although invasive electrodes are sometimes used such as in electrocortiography. EEG measures voltage fluctuations resulting from ionic current within the neurons of the brain . EEG refers to the recording of the brain's instantaneous electrical activity over a time period , recorded from many electrodes placed on scalp.

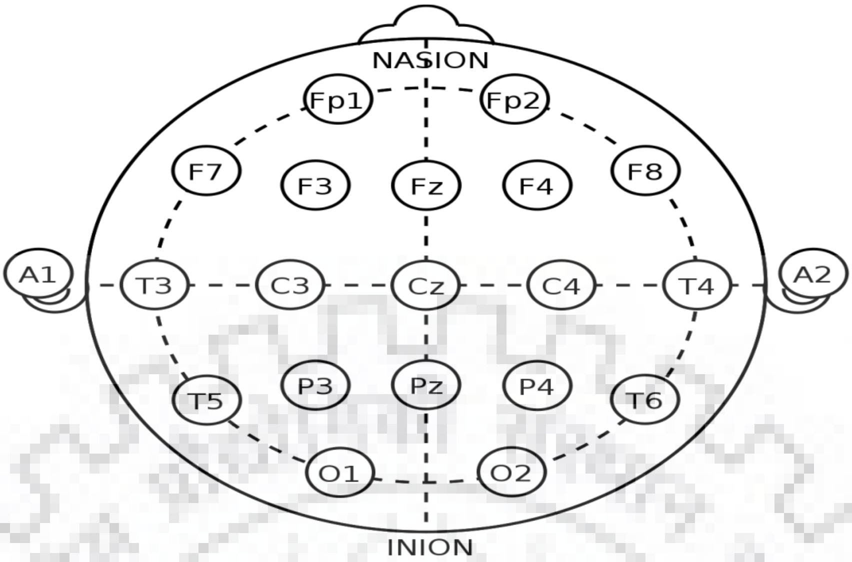


Figure 1.2: 10-20 arrangement of EEG placement on scalp [2]

EEG signal can be of 5 frequency bands that represent various states of minds. The frequency bands are given in the following table :

Delta	0.5<f<4 Hz
Theta	4<f<8 Hz
Alpha	8<f<13 Hz
Beta	13<f<28 Hz
Gamma	28<f<40 Hz

Table 1.1: EEG signals with different frequencies and their frequency range

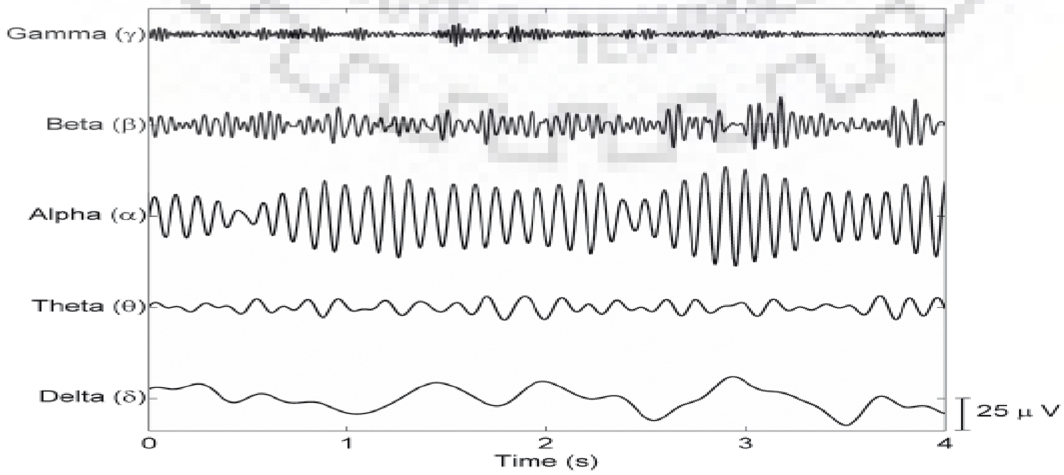


Figure 1.3: EEG signal waveform at different frequencies[3]

1.3. Event related potential

An event related potential is the measured response that is the result of a specific event that can be sensory, motor or cognitive in nature. This response is electrophysiological in nature and is given to a stimulus. ERP's are measured by the means of EEG, but the can be several other methods that can be used such as magneto-encephalography (MEG) but the in that is equivalent of ERP is the ERF, or the event-related field. Evoked potentials and induced potentials are subtypes of ERPs. ERP research is much cheaper to do than other imaging techniques such as fMRI, PET etc. The reason for that is purchasing and maintaining an EEG system is less expensive than the other systems. ERPs can be efficiently measured using EEG, a procedure that measures electrical activity of the brain over a period of time using electrodes that are placed on the scalp.

The EEG represents thousands of simultaneously ongoing brain processes. This means that the brain response to a single stimulus or event of interest is not usually visible in the EEG recording of a single trial. To see the brain's response to a stimulus, the experiment must be conducted for many trials and average of the results must be taken causing random brain activity to be averaged out and the relevant waveform to remain, which is called the Event related potential.

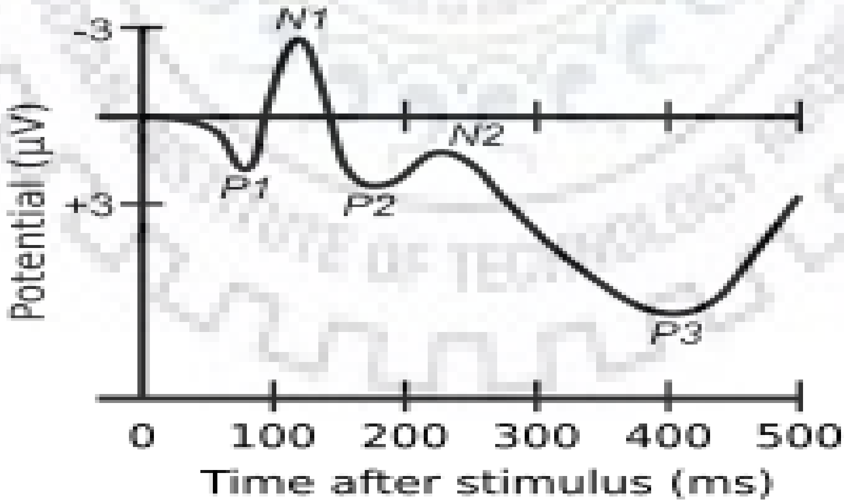


Figure 1.4: A waveform showing several ERP components [4]

1.3.1. Some advantages that ERP signal analysis are:

1) **Relative to behavioural measures**

Compared with behavioural procedures, ERPs provide a continuous measure of processing between a stimulus and a response, making it possible to determine which stage is being affected by a specific experimental manipulation. Another advantage over behavioral measures is that they can provide a measure of processing of stimuli even when there is no behavioural change. However, because of the significantly small size of an ERP, it usually takes a large number of trials to accurately measure it correctly.

2) **Invasiveness**

   Unlike microelectrodes, which require an electrode to be inserted into the brain, that expose humans to radiation, ERPs use EEG, a non-invasive procedure.

3) **Cost**

   ERP research is much cheaper to do than other techniques. This is because purchasing and maintaining an EEG system is less expensive than the other systems.

1.4. Emotion recognition using EEG signals

Emotion refers to the changes in the psychological and physical state as a reaction to internal or external stimulus event, but there is no common consensus on the definition of emotion. Not just that, but also there is an overlap among the concepts of emotions , feeling and mood. One of the important issues in this area is how to represent emotions.
There are numerous methods for emotion depiction , but there is no agreement which must be used. Most methods for emotion depiction comes under one of the two major approaches, the simplest one is to use distinct words for each emotion, and the other one is to represent emotions through multi-dimensions scales. Emotional recognition is a very effective method to measure the cognitive activity of brain because the generation of emotions is done by brain and through various methods of study we can find out the trends displayed by brain during different situations which we face by doing analysis of the emotions that we depict in that situation.

1.5. **Literature survey**

As we have discussed about the cognition, cognitive science and emotional recognition so as a part of my literature survey we have studied about the various methods and techniques to measure cognitive activity, the theories of cognition and methods to do emotional recognition. The part of my work is based on EEG signals but the methods that have been discussed will be alternative methods to do these tasks like using visual power or using any other biomedical signal also.

1.5.1. Theories of cognitive recognition

1.5.1.1. Viewpoint-invariant theory

Viewpoint-invariant theory suggests that object recognition is based on structural information, for eg individual parts, allowing for cognitive recognition to take place regardless of the object's viewpoint. Similarly, recognition is possible from any viewpoint as individual parts of an object can be rotated to fit any particular view. This form of recognition requires little memory as only structural parts need to be studied , which can produce multiple object depictions through the inter-relations of these parts.

1.5.1.2. Recognition by components

An extension of Marr and Nishihara's model, the recognition by component theory given by Biederman in 1987 states that visual information gained from an object is divided into simple geometric shapes , such as blocks and cylinders, also known as "geons" (geometric ions), and are then matched with the most similar object depiction that is stored in memory to provide the object's identification.

Figure 1.5 : two cases of inter-related “geons” [5]

1.5.1.3. View-point dependent theories

This model, proposed by Marr and Nishihara (1978), states that object recognition is achieved by matching 3-D model depictions obtained from the visual object with 3-D model representations stored in memory as shape precepts. Through the use of computer programs and algorithms, Yi Yung-feng in 2009 was able to demonstrate the ability for the human brain to mentally re-construct 3D images using only the 2D images that appear on the retina. Their model also demonstrates a high degree of shape consistency conserved between 2D images, which allow the 3D image to be reconstructed.

1.5.1.4. Multiple views theory

This theory proposes that object recognition depends upon the viewpoint continuously where each viewpoint is recruited for different types of recognition. At one extreme of this continuum, viewpoint-dependent mechanisms are used for within-category discriminations, while at the other extreme, viewpoint-invariant mechanisms are used for the categorization of objects.

1.5.2. Methods for emotional recognition

Emotion refers to the changes in the psychological and physical state as a response to internal or external stimulus event, but there is no widespread consensus on the definition of emotion. Not just that, but also there is an overlapping among the concepts of emotion, feeling and mood. One of the important issues in that research area is how to represent emotions.

There are numerous methods for emotion representation, there is no agreement which must be used. Most methods for emotion representation comes under one of two major approaches, the simplest one is to use distinct words for each emotion, and the other one is to represent emotions through multi-dimensions scales

1.5.2.1. Discrete categories approach

In this approach emotions are represented with distinct types, such as anger, fear and happiness. It is closer to common sense of human beings, but the main difficulty in this approach is that there is no global agreement on which categories are to be used. Further,

there are difficulties in translating this categories between different individuals, the word that presents an emotion for a individual may have no equivalent in an another culture .
An example of researchers that try to define these categories is Ek-man and Friesen etal., where they have defined six basic emotions: “happiness, surprise, sadness, fear, disgust and anger “. Emotions recognition by this approach is considered a classification problem.

1.5.2.2. Multi dimensions space approach

In this approach, emotions are depicted through a number of scales, each scale is considered as a dimension in a multi-dimension space. Each scale has a maximum and minimum value, and it can be discrete or continuous. A specific emotion can be defined by a combination of values for each scale or a point in the multi-dimension space , so a person can concentrate his attention on the emotion recognition without any worry about which emotion categories have to be used.
One of the most used models in this approach is the valence-arousal model. In this model, emotions are represented by a space of two dimensions, the first one is the valence scale ranged from pleasant to unpleasant and the second one is the arousal scale ranged from active to inactive , a third scale can be added to that model , the dominance scale ranged from dominant to submisive.
An example for the use of dominance scale is to differentiate between emotions like anger and fear because they are very similar to each other in terms of valence and arousal scales, but they are distinct in terms of dominance scale, i.e. anger has an extreme value in the direction of dominant, whereas fear has an extreme value in the direction of submissive .
Both valence arousal space and valence-dominance space with some examples of emotion classification mapped on them. In this approach, researchers can consider each scale as a regression problem, or split each scale into number of levels, and consider it as a classification problem.
A common example of splitting each scale is to split the valence-arousal space into four quadrants: high valence with low arousal (HVLA), high valence with high arousal (HVHA), low valence with low arousal (LVLA) and low valence with high arousal (LVHA).

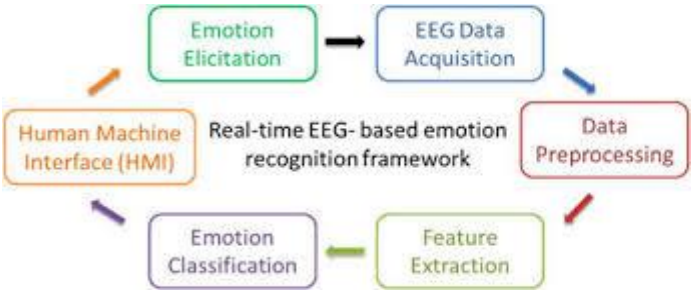


Figure 1.6: process of emotion recognition using EEG [6]

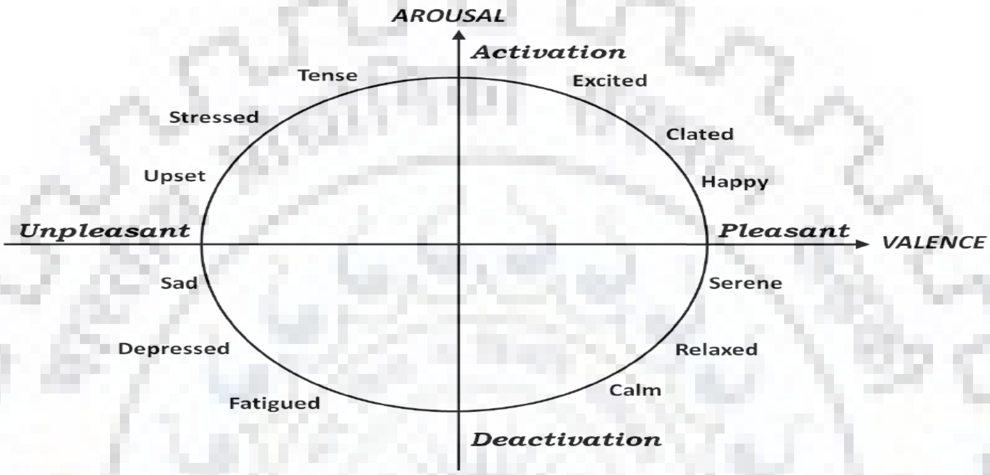


Figure 1.7: valance arousal space representing series of emotions. [7]

1.5.3. DEAP (database for emotional analysis using physiological signals)

The DEAP data set give us the stimulus that is needed for the cognitive analysis by studying the emotional trends of a person [8]. Though in DEAP data set many physiological signals are used but we will be keeping our discussion to the EEG signals only. In the work previously carried out , music video clips are used as the stimuli to depict different emotions. To this end, a relatively large set of video clips was gathered using a particular stimuli selection method. A subjective test was then performed to select the most appropriate test material. For each video, a one-minute highlight was selected automatically. 32 participants took part in the experiment and their EEG and peripheral physiological signals were recorded as they watched the 40 selected music videos. Participants rated each video in terms of arousal, valence, dominance and familiarity. The database contains all recorded signal data, frontal face video for a subset of the participants and subjective ratings from the participants. Also included is the subjective ratings from the initial online subjective and the list of 120 videos used.

In the DEAP DATA set the relevance vector machine (RVM) algorithm is used to obtain different values of valance and arousal for different participants according to the EEG graphs obtained by showing different stimulus to them. Based on this experiment we can find out what kind of emotion is shown by a person when a particular kind of stimulus is given to him to perceive and then in what mental state his mind is in and then how these emotions or mental states repeat themselves for different persons and wheatear they are same or vary for person to person.

1.5.4. Previous work done

Over a period of time lot of research is being done in the areas of measuring brain activity and EEG signals that can be acquired through the human scalp. Below we have represented all the work that has been previously done in a tabular form.

S.NO	Author and year	Title	Objective	Findings
1.	Alan S., Gavin's, etal. (1975)	Analysis of the electrical activity of the human brain using EEG	correct difficulties due to high dimensionality of EEG signals	Applying interactive, real time analysis system supporting visual interpretation based features and prefer automated classification. [9]
2.	Grant B.Anderson. (1975)	Analysing the level of Anesthesia by analysis of spontaneous EEG activity.	Usability of developing a EEG computer- based pattern recognition system which can continuously estimate the level of anesthesia of patients during operation.	systems based on the recognition of frequency domain EEG patterns were developed to find the pattern related to the level of anesthesia. [10]

3.	James e.Lenz (1981)	Computer based measurement and calibration of EEG DATA acquisition system	Computer based measurement and calibration of an EEG data acquisition system	Simulation of time series with known spectral characteristics, to measure and verify the frequency and phase response of system. [11]
4.	Andres, Isaksson (1981)	Analysis of EEG signals along with parametric models	Find out the vital properties of EEG, and find out the influential factors.	Analysis using parametric models of EEG signals. The scalar multivariate model is linear, with parameter being either time variant or invariant. [12]
5.	Gregory w., Neat. (1990)	System description of EEG- based brain to computer communication	Decoding device designed to develop and evaluate EEG-based communication.	The resulting device forms a complex dual control structure in which both device and the user adapt to achieve the fast and accurate control of movement of cursor. [13]
6.	John R, La Course (1990)	Communication controlled system for the disabled using eye movement.	EEG based communication for persons who are severely	This paper is based on the design and capability of the discrete electro-

			handicapped	oculographic control system. [14]
7.	Jamie A., Pineda (2003)	To control brain rhythms by making a brain computer interface	To find the ability of subjects to manipulate the sensory motor rhytms in the context of visual depiction of single feedback signal.	A BCI based on a binary signal is possible. During a task subjects learned to control levels of mu activity faster. This suggests control of each hemisphere is possible. [15]
8.	Roman, Krepki, (2007)	The Berlin brain-computer interface (BBCI)- towards a new communication n channel for online controlling gaming applications	EEG-BCI based computer game control.	It introduces Berlin BCI and presents set ups where the user is provided with intuitive control strategies that use feedback. A diversity of multimedia such as computer games, and their specific control tactics, such as VR (virtual reality) scenarios are open for research. [16]
9.	Gernot R., Muller-Putz (2008)	SSVEP based BCI to control electrical prosthesis.	To restore the grasp in spinal cord injuries control of neuro-prosthetic devices	A self based 4 class BCI based on steady state visual evoked potentials to control two-ax electrical hand prosthesis. [17]

10.	Laurent, George (2011)	Using bio-signals from scalp to control an object-design and evaluation	Electrical bio-signals are measured on scalp corresponding to relaxation and some task to control a object in a video game.	Combination of brain and muscular activity performance can be improved for the following system.[18]
11.	Sun Sheng jie (2014)	Two player EEG- based Neuro-feeback ballgame for attention enhancement	Quantizing the attention level using the ratio of theta to beta band power in EEG signal.	The experimental analysis shows that the proposed game is capable of enhancing players attention skills [19]
12.	Oberdans R., Pinherio (2016)	Wheelchair simulated game for helping disabled people.	Wheelchair simulated game for training people who have severe disabilities.	EEG motor movement/ imagery dataset , captured by the BCI 2000 system and EEG samples from 10 persons were used for the model to make 3 dimensional simulation environment for intelligent wheelchair control. [20]
13.	Pradeep, kumar (2017)	Neuro-phone: An assistive framework to operate smartphone using EEG signals.	An assistive framework “Neuro-phone” to operate smartphone using EEG signals by person with	EEG signals of 9 mental commands from 8 participants are recorded using an android smartphone.

			disability.	Accuracy of 68.69 percent is achieved.[21]

TABLE 1.2: previous work done in the field of cognition using EEG signal analysis

1.6. Problem statement

In the literature survey we have studied about the various theories of cognition, various trends representing the emotional classification, various methods by which modelling of the emotions can be done, and about the DEAP data set which is available universally which provides a structural method to carry out the cognitive analysis of the brain using emotions.

But the problem remain so far is that there is not any precise method being implemented or used which clearly depicts the emotions in a structured form numerically or graphically and provide proper analysis of the brain’s activity when it faces a particular situation.

So there is need of a novel method to be developed which can give proper analysis of the emotions using the techniques that are accurate, precise and can be done in a laboratory. Along with that it needs to be cost effective to. By this emotional analysis we can find an effective way to measure cognitive activity of the brain.

1.7. Plan of work

In our work we have used the multi fractal detrended fluctuation analysis (MFDFA) on EEG signals that we acquire from DEAP data set. In this first we will make a butter-worth filter (bandpass) with the sampling frequency of 128 Hz..We have taken 32 videos of 1 minute duration through 32 EEG channels. We have used db 10 wavelet at level 20 for the purpose of decomposition of EEG signals. Though EEG signals consist of 5 frequency bands but in this study we have taken only three frequency bands i.e. 1) beta 2) alpha 3) theta . Using these frequency bands we have to calculate the two components for our analysis purpose – 1) Singularity component 2) Hurst component.

Then we will do further analysis by calculating the features. These features are nothing but the mathematical modalities of our EEG signal that has been generated through 32 channels which is available to us already in the DEAP data set. Once these features are calculated we can get the idea what parameters are obtained for different channel, different frequency and different feature that we select by comparing them to each other

The data-set that we will be using for our work consists of 32 videos of 1 minute duration as stated above . the description of videos and data set is given below-

Artist	Title
1. Jungle Drum	http://www.youtube.com/watch?v=iZ9vkd7Rp-g
2. Scotty Doesn't Know	http://www.youtube.com/watch?v=51ncDQYxsm8
3. Blame It On The Boogie	http://www.youtube.com/watch?v=nb1u7wMKywM
4. Love Shack	http://www.youtube.com/watch?v=leohcvmf8kM
5. Song 2	http://www.youtube.com/watch?v=WlAHZURxRjY
6. First Date	http://www.youtube.com/watch?v=vVy9Lgpg1m8
7. Satisfaction	http://www.youtube.com/watch?v=eoRiVwFP02s
8. Fuck You	http://www.youtube.com/watch?v=S0zMHf7J15g
9. I Want To Break Free	http://www.youtube.com/watch?v=EVYgRPfC9nQ
10. Bombtrack	http://www.youtube.com/watch?v=Tu1wAP2Baco
11. Say Hey (I Love You)	http://www.youtube.com/watch?v=eoaTl7IcFs8
12. Miniature Birds	http://www.youtube.com/watch?v=_iEnN9ip1Qk
13. First Day Of My Life	http://www.youtube.com/watch?v=zwFS69nA-1w
14. I'm Yours	http://www.youtube.com/watch?v=EkHTsc9PU2A
15. Butterfly Nets	http://www.youtube.com/watch?v=B8eI64H1Cqk
16. Darkest Things	http://www.youtube.com/watch?v=ijLKoqN5_EY
17. Moon Safari	http://www.youtube.com/watch?v=kxWFyvTg6mc
18. What A Wonderful World	http://www.youtube.com/watch?v=3orLNBS2ZbU
19. Me Gustas Tu	http://www.youtube.com/watch?v=mzgjiPBCsss
20. Love Story	http://www.youtube.com/watch?v=8xg3vE8Ie_E
21. Gloomy Sunday	http://www.youtube.com/watch?v=KzWVWY5QUzg
22. Normal	http://www.youtube.com/watch?v=A-BSL5Av89w

23. How To Fight Loneliness http://www.youtube.com/watch?v=zLDPhPrr5Ig
24. Goodbye My Lover http://www.youtube.com/watch?v=wVyggTKDcOE
25. Goodbye My Almost Lover http://www.youtube.com/watch?v=EDEEzS7OV2k
26. The Weight Of My Words http://www.youtube.com/watch?v=G-k19OCq7vE
27. Rain http://www.youtube.com/watch?v=15kWlTrpt5k
28. Breathe Me http://www.youtube.com/watch?v=ghPcYqn0p4Y
29. Hurt http://www.youtube.com/watch?v=zHqZmtAD0lQ
30. May It Be (Saving Private Ryan) http://www.youtube.com/watch?v=xxvw5vrJxos
31. The One I Once Was http://www.youtube.com/watch?v=O0yoxveh7Tg
32. The Beautiful People http://www.youtube.com/watch?v=Ypkv0HeUvTc

Table 1.3: List of videos used for the EEG signal analysis. These all are from DEAP data set

Using these videos we will do EEG signal analysis and then further will be able to do emotional classification

Chapter 2.MFDFA based emotional classification

2.1. Introduction

In this technique we have used the multi fractal detrended fluctuation analysis on EEG signals that we acquire from DEAP data set. In this first we will make a butterworth filter (bandpass) with the sampling frequency of 128 Hz.. We have taken 40 videos of 1 minute duration through 32 EEG channels. We have used db 10 wavelet at level 20 for the purpose of decomposition of EEG signals. Though EEG signals consist of 5 frequency bands but in this study we have taken only three frequency bands i.e. 1) beta 2) alpha 3) theta . Using these frequency bands we have to calculate the two components for our analysis purpose – 1) Singularity component 2) Hurst component.

Characteristics of a biomedical signal are visually apparent but they are not captured by common methods like average amplitude of the signal. A biomedical signal is a time invariant signal which repeats itself after certain interval of time.

Fractal analysis estimates the power law exponent 'H' that define the particular kind of scale invariant structure of the biomedical signal. Fractal analysis are often used in biomedical signals to define the scale invariant structure of ECG, MRI AND X-ray images.

Mono-fractal and multi-fractal structures of bio-medical signal are scale in-variant structures. Mono-fractal structures are defined by a single power law exponent and assumes that scale invariance is independent of space and time. Spatial and temporal variation in scale structure of biomedical signal often appears. These spatial and temporal variations indicate a multi-fractal structure that is defined by the multi-fractal spectrum of power law exponents.

2.2. Implementation of MFDFA in matlab

The implementation of MFDFA involves the following steps in MATLAB –

2.2.1. Convert noise like time series into the walk like time series.

The random walk consists of a mono-fractal component and a multi-fractal component. The fractal property is defined by their likeliness with respect to each other. If biomedical series is in the noise form than it must be converted into random walk form by studying the hills and valleys of the given biomedical series. This can be done by applying the detrended fluctuation analysis to the series. for that we have to subtract the mean value and then further integrate the time series.

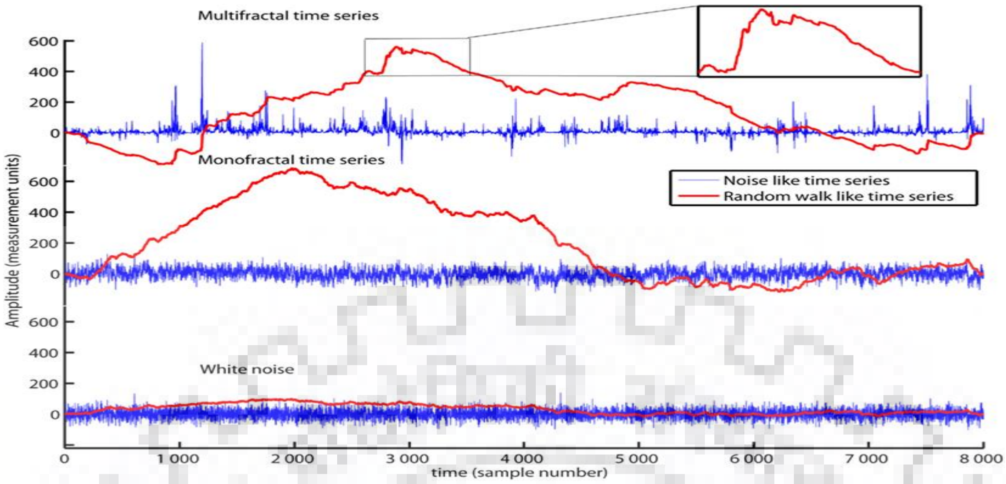


Figure 2.1 : the time series represented by upper panel is multi-fractal represented by middle panel is mono-fractal and by lower panel is white noise. [22]

2.2.2. Compute the RMS value of the biomedical time series.

One of the most conventional method for the analysis of the biomedical series is that to calculate the root mean square value of the whole series. we can calculate the RMS values of all the series that are mono-fractal, multi-fractal and white-noise. Further with the help of MFDFA we can differentiate in between these structures.

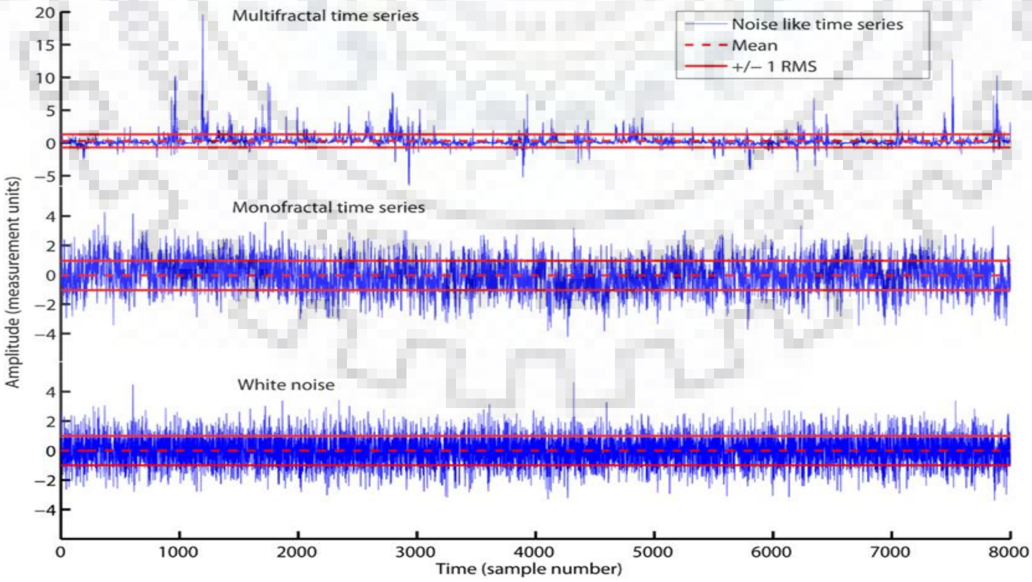


Figure 2.2 : The time series with RMS (red solid lines) and zero average (red dashed lines). First panel is for multi-fractal, second is for mono-fractal and third id for white noise. [22]

2.2.3. Compute local fluctuation in time series with non-overlapping segments.

Trends that have slow variations are always present in a biomedical time series. therefore by de-trending of the series we can calculate the scale invariant structure and the variation around these trends.

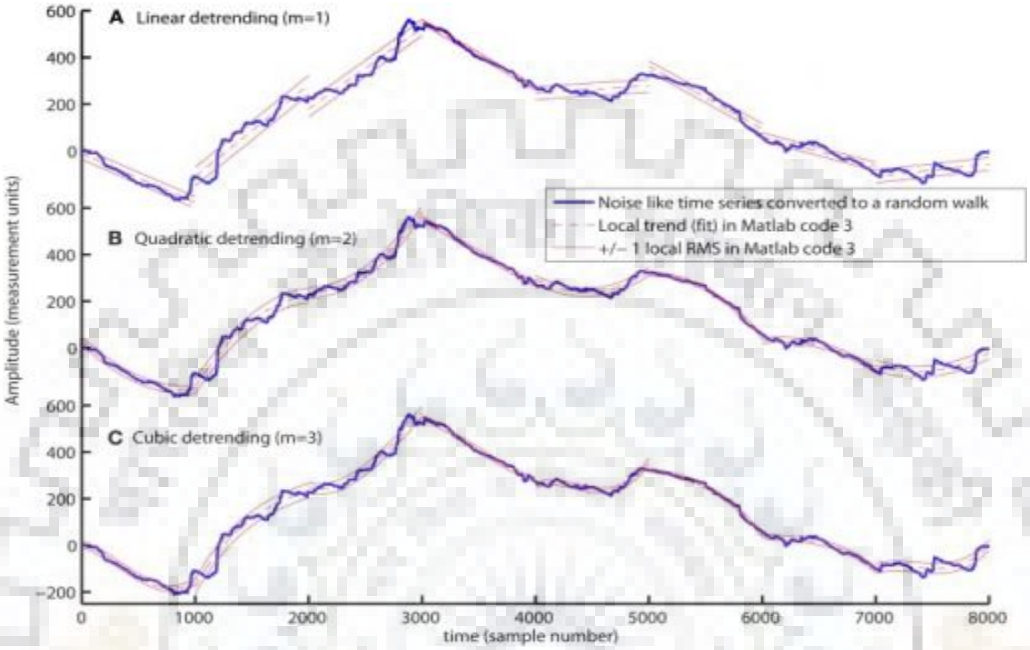


Figure 2.3 : Trends changing with change in order. The fluctuations vary according to the order of the trend if order 1 then we obtain linear de-trending, if order is 2 then we obtain quadratic de-trending, if order is 3 we obtain cubic de-trending. [22]

2.2.4. Compute local RMS around trends that are encountered in biomedical time series.

Multi-fractal time series have fluctuations with both respect to the large and small magnitudes. RMS in MATLAB can be computed for segments of the time series to differentiate between the local fluctuations. The procedure is to cut the entire series into equal sized samples and then compute RMS for each individual sample.

2.2.5. Summarise amplitudes of local RMS into an overall RMS

The variations can be summarised by an overall RMS. The fast changing fluctuations in the time series will influence the RMS for segments with smaller sample sizes and the slow changing fluctuations in time series will influence the segments with larger sample sizes. Therefore we show should accommodate both slow changing and fast changing fluctuations so as to show the trends of large and small sample sizes.

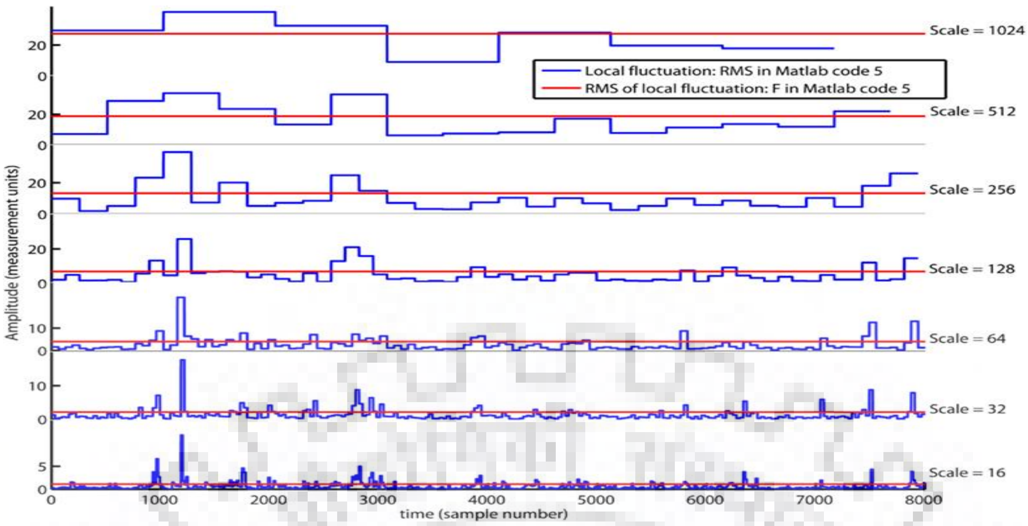


Figure 2.4: local fluctuations computed for several sample sizes [22]

2.3. Hurst and singularity exponent

MFDFA is based on the calculation of the various parameters that can be computed and then can be further analysed of a biomedical time series. These parameters are necessary to find out the nature of the biomedical series and thus using that we can calculate the various features required to describe various states of mind.

For MDFA we need to calculate two exponents which are very crucial for our analysis purposes are - 1. Hurst exponent 2. Singularity exponent

2.3.1. Hurst exponent

Power law relation defined by the overall RMS for multiple segment sample sizes is defined by the MFDFA and is called as the Hurst component. In MFDFA of the time series the Hurst component is obtained by the q-order extension of the overall RMS. The power law relation between the q- order RMS is identified as the q-order Hurst component. It defines a series which has both the components of a noise like series as well as random walk like series in time domain. The values for Hurst component lies between 0-1 for noise like series and above 1 for random walk like series. if the value of Hurst component lies between .5-1 it means that the series has a long range dependent structure. If the value of Hurst exponent lies between 0-.5 then it has a short range dependent structure or independent structure. According to results obtained previously the white noise has an independent structure with Hurst exponent has value close to .5 whereas the independent structure is obtained for mono-fractal and multi-fractal with

Hurst exponent in between .7-.8. though mono-fractal and multi-fractal time series have similar RMs values and Hurst components the overall structure of both the series is quiet different. With no fluctuations in small and large components mono-fractal time series has normal distribution. Whereas multi-fractal components don't have normal distribution due to large fluctuations and thus all the components are needed to be considered.

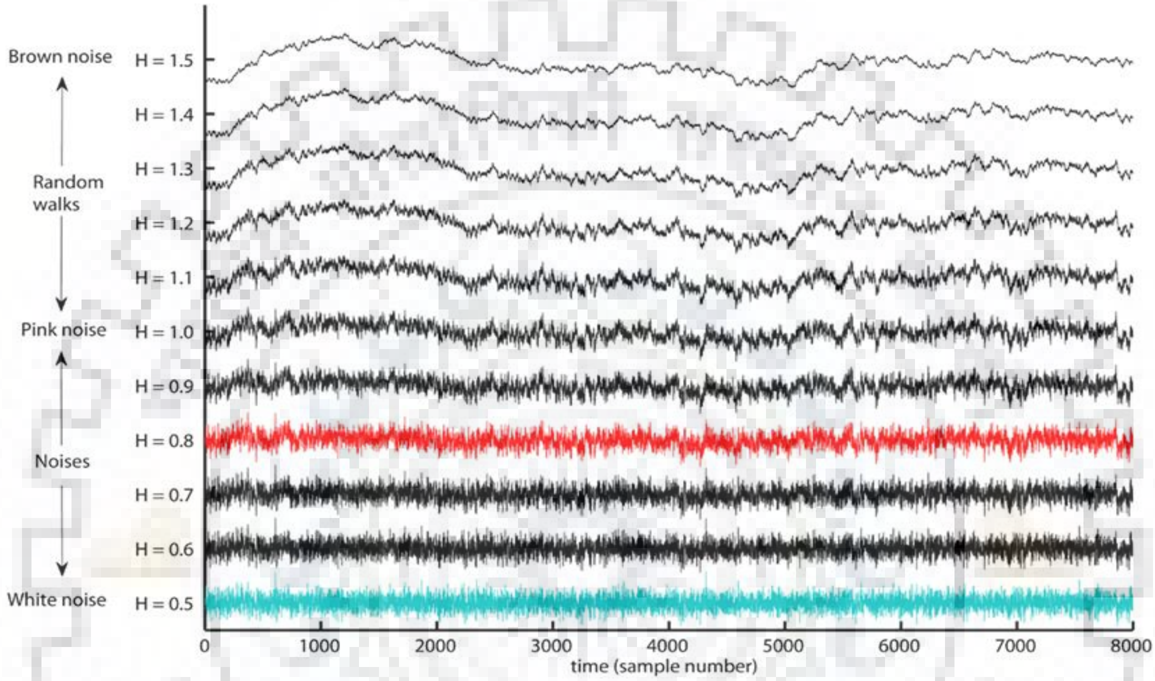


Figure 2.5: range of Hurst exponents [22]

2.3.2. Singularity exponent

Singularity exponent is used in MFDFA to describe the fractal dimension of a subset of a points of a function belonging to a group of points that have same holder's exponent. Basically a singularity exponent defines how much a fractal points there are in a function. More formally the singularity exponent the singularity exponent is defined as –

$D(\alpha) = D_f \{ x, \alpha(x) = \alpha \}$ ....eqn(1)

Where $\alpha(x)$ defines holder exponent .

The holder exponent is defined by the space in d-dimension where real or complex valued functions fulfil the following condition –

modulus of (f(x) – f(y)) ≤ C modulus of (x-y)∝.......................eqn(2) where $\propto$ is > 0 if $\propto$ is greater than 1 than the function applied in that particular period

if $\propto = 1$ then the function satisfies the condition that the first order derivative of the function applied in that region is constant

for any $\propto$ $0 < \propto < 1$ the function is uniformly continuous.

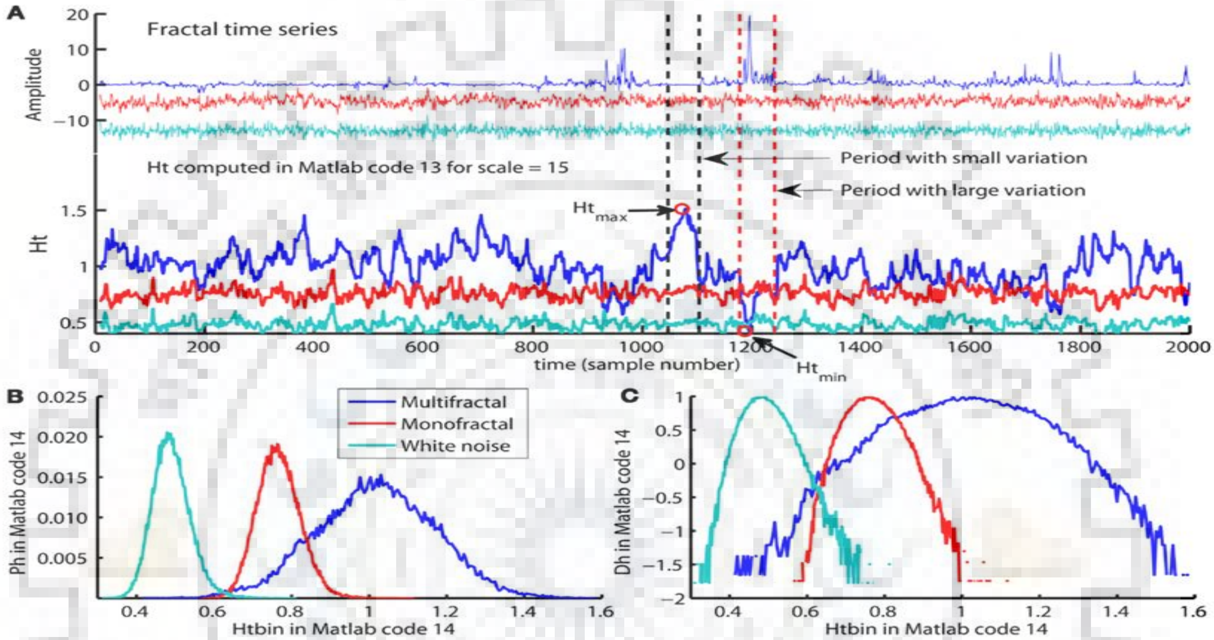


Figure 2.6: A: multi-fractal, mono-fractal, white-noise series with their local Hurst exponents. B: probability distribution of the calculated Hurst exponents [22]

2.4. q order and m order exponents

Now these two components can be of q order as well as the m order. The difference between q order and m order is as follows-

2.4.1. q order

weighing of the local fluctuation is decided by the parameter q. For weighing the periods in small and large variations the q order must have both positive and negative orders in q. With the increase in orders of q either positive or negative the precision decreases, therefore larger orders must be avoided to avoid numerical errors. Stability also depends on the difference between largest variation and smallest variation in a multi-fractal spectrum. The higher is the difference lesser is the stability and vice-versa. Stability is also dependent on the sample size present in the series. series having larger sample size is more stable as compared to the series having the smaller sample sizes. Another advantage that larger sample sizes offer are if the sample size is large higher order of q can be used and stability wouldn't be affected much. Minimum sample size for MDFA must be 1000 samples.

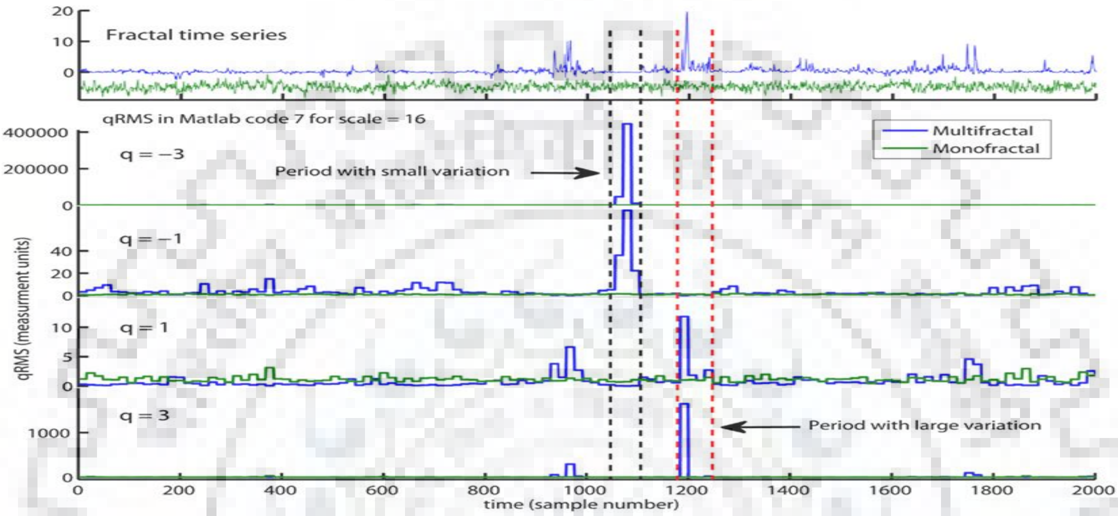


Figure 2.7 : q order series with their local fluctuations note that when q= -3 the fluctuation is large for smaller sample sizes but for q = 3 and large sample sizes fluctuation is less. [22]

2.4.2. m order

Another way to compute local RMS in MFDFA is around a polynomial and its shape is defined by the order m of the polynomial. As the order m will increase the shape will become complex and it will not befitted to small sample sizes. The order 1-3 is sufficient if the series that we will be using has 10-20 samples. The trends can be of oscillatory in nature or of ramp liked shape and not necessarily be polynomial for biomedical time series in MFDFA. MFDFA can also be done using other procedures such as wavelet decomposition

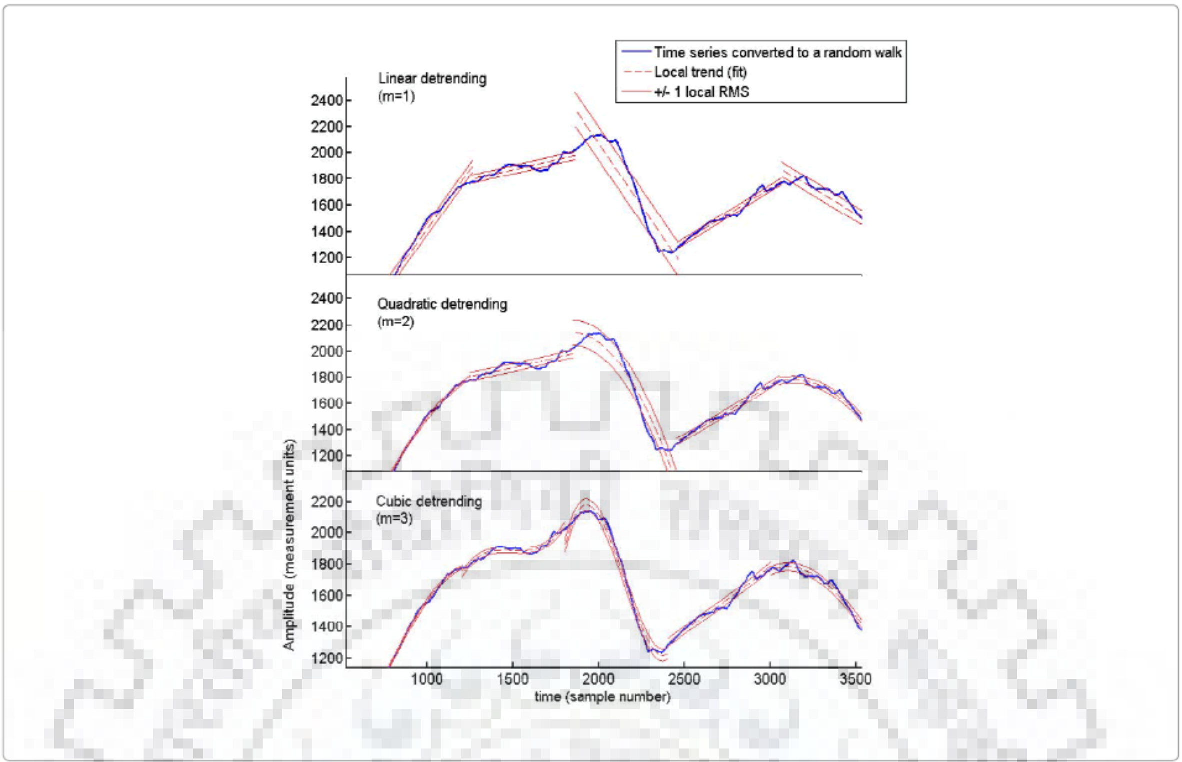


Figure 2.8: m order MFDFA analysis [22]

2.5. MFDFA code application on the DEAP DATA SET

Now we have written a code for MFDFA analysis for the 40 video samples that are available to us which will generate 2 cells of 1*40 for each video, one for the Hurst exponent and one for the singularity exponent. The code is written below in the form of flow chart

Define a butterworth (band pass) filter of cut of frequencies 1 and 45

↓

Load the file that is needed to be analysed

↓

For video channels 1:40 select the period that is needed to be analysed.

↓

Define the wavelet's name and the level for decomposition. wavelet Name='db10'   level=20.

↓

Apply wavelet decomposition for the three frequency bands 1. Beta 2 Alpha 3 theta

↓

Define Hurst and singularity exponent mathematically and run the code to generate data from it

↓

Save the final file generated in FN=strcat ('DEAP_MFDFA\',Name,'.mat')

Figure 2.9: MFDFA code in MATLAB

With the help of this code MFDFA analysis is done and both Hurst an singularity exponent is generated. Now for further analysis and to generate the results for different features we will use the obtained data from MFDFA.

Chapter 3 Feature extraction

Now we will do further analysis by calculating the features. These features are nothing but the mathematical modalities of our EEG signal that has been generated through 32 channels which is available to us already in the DEAP data set. Once these features are calculated we can get the idea what parameters are obtained for different channel, different frequency and different feature that we select by comparing them to each other.

3.1. Data processing and supervised learning

The purpose of data processing is to break down it into several tasks. We will perform feature extraction, selection and classification. Features can be acquired from various characteristics of the signal. We will be using frequency domain mainly to derive our features. [23]

3.1.1. Feature extraction

The purpose of feature extraction is to convert the input signals into a set of characteristics which are very similar to the signals of the identical category and distinct for signals of distinct categories. It leads to the idea of obtaining features that are invariant to transformations such as rotation and scaling of the signal. Feature selection is the process of selecting a subset of features from a given set of extracted features which represents the input signal. In this discussion, features related to cognitive science and features used to study cognitive activity of the brain using EEG signal analysis were extracted and analysed.

3.1.2. Feature dimensionality reduction

We need to understand which feature is sufficient and appropriate to a particular problem but it is usually not necessary to know which feature will be useful. It is here the feature selection methods play a very critical role. Feature selection techniques can be useful to accomplish these tasks-

i) Reduce the size of the feature matrix. It might involve removal of some features and reduction of the data storage.

ii) Improving both the computational cost as well as the performance of the classifier, since we only store the features that are useful to the classifier.

This means that we do not choose the most relevant, because the design could be non-optimal or alternatively the most useful because it may exclude the most useful features. Dimensionally, low dimension features are derived from input features. It is desirable to keep the dimensionality of the features selected as low as possible , to make the system more reliable and robust.

3.1.3. Feature selection of EEG signal

Feature selection is an essential step in a classification system. Reducing the number of features can be done by feature selection, in which a subset of feature is chosen to make the classification accuracy maximum. There are two types of feature selection methods: wrapper approach and filter approach. In wrapper approach, the feature selection is coupled with a particular classifier. The feature selection criteria is to minimise the classification error.

In filter approach the goal is to optimise a criterion that is independent of classifiers. For example Mutual information between input features and class labels is a highly used criterion for filter approach as it is related to upper and lower bounds of Bayes error. On the other hand, the wrapper approach is accurate to a selected classifier, but is not flexible. Moreover, the selection procedure involves combination, complexity of training and testing, hence is very intensive, and is not optimum for the online systems. Hence when using a cluster of classifiers, the filter approach is preferred for low computational costs.

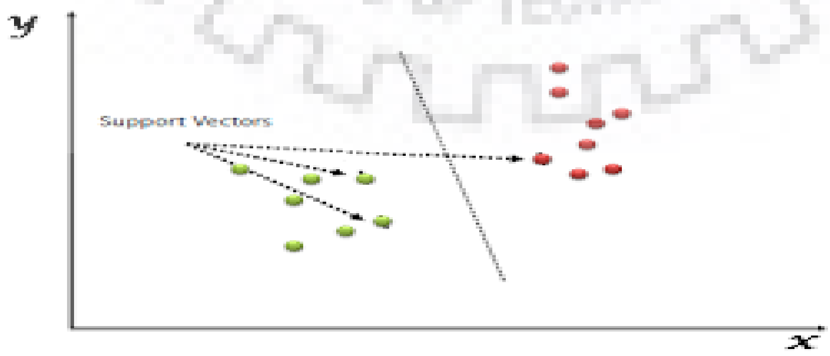


Figure 3.1: **support vector machines an example of supervised learning model used for classification [24]**

3.2. Selection of features

The features that we took are-

1. Mean = m $\qquad m = \frac{1}{n} / \sum_{k=1}^{n} xk$ (eqn3)
2. Standard deviation = s.d. $\qquad s.d. = \sqrt{\frac{\sum_{k=1}^{n} xk - m}{n}}$ (eqn4)
3. Average curve length = C.L. $\qquad C.L. = 1/n \sum_{k=2}^{n} xk - xk - 1$ (eqn5)
4. Average energy = E $\qquad E = 1/n \sum_{k=0}^{n} xk * xk$ (eqn6)
5. Average Teager energy = TE $\qquad TE = 1/n = \sum_{k=0}^{n} xk - 1 * xk - 1 - xk * xk - 2$ (eqn7)
6. Skewness = (x_{skew}) $\qquad x_{skew} = \frac{\sum_{k=0}^{n} (xk-m)\hat{}3}{(n-1)\ s.d.\hat{}3}$ (eqn8)
7. Kurtosis = (x_{kur}) $\qquad x_{kur} = \frac{\sum_{k=0}^{n} (xk-m)^4}{(n-1)\ s.d.\hat{}4}$ (eqn9)
8. Shape factor = S.F. $\qquad S.F. = x_{rms}/1/n \sum_{k=0}^{n} sqrt(xk)$ (eqn10)
9. Minimum = x_{min} $\qquad x_{min} = \min(x_k)$ (eqn11)
10. Root mean squared value = x_{rms} $\qquad x_{rms} = 1/n \sum_{k=0}^{n} xk\hat{}2$ (eqn 12)
11. Geometric mean = G $\qquad G = n\sqrt{x1} * x2 * \ldots\ldots xn$ (eqn 13)
12. Harmonic mean = H $\qquad$ H = n/(1/x1+1/x2......1/xn) (eqn 14)
13. Range = R $\qquad$ R = xn-x1 (eqn15)
14. Coefficient of variation = DK $\qquad$ DK = (S/m)*100 (eqn 16)
15. Standard error = S_x $\qquad S_x = s/\sqrt{n}$ (eqn17)
16. Median = x $\qquad x = (x_{k+1/2})/2$ (eqn18)
17. 25% trimmed mean = t25 $\qquad$ t25 = trimmean(x,25) (eqn19)
18. 50% trimmed mean = t50 $\qquad$ t50 = trimmean (x,50) (eqn20)
19. Interquartile angle (IQR) $\qquad$ IQR = iqr(x) (eqn21)
20. Mean absolute division (MAD) $\qquad$ MAD = mad(x) (eqn22)
21. Central moments (CM) $\qquad$ CM = moment (x,10) (eqn23)
22. Sign test (p,n) $\qquad$ (p,n) = signtest(x) (eqn24)
23. Hjort parameters – activity(A) $\qquad$ A = S^2 (eqn25)
24. Hjort parameters - mobility (M) $\qquad$ M = S1^2/S2^2 (eqn26)
25. Hjort parameters – complexity (C) $\qquad$ C = sqrt (s2/s1^2 – s1/s^2) (eqn27)

3.3. Feature extraction in MATLAB.

Now we extract these features by writing the code in MATLAB –

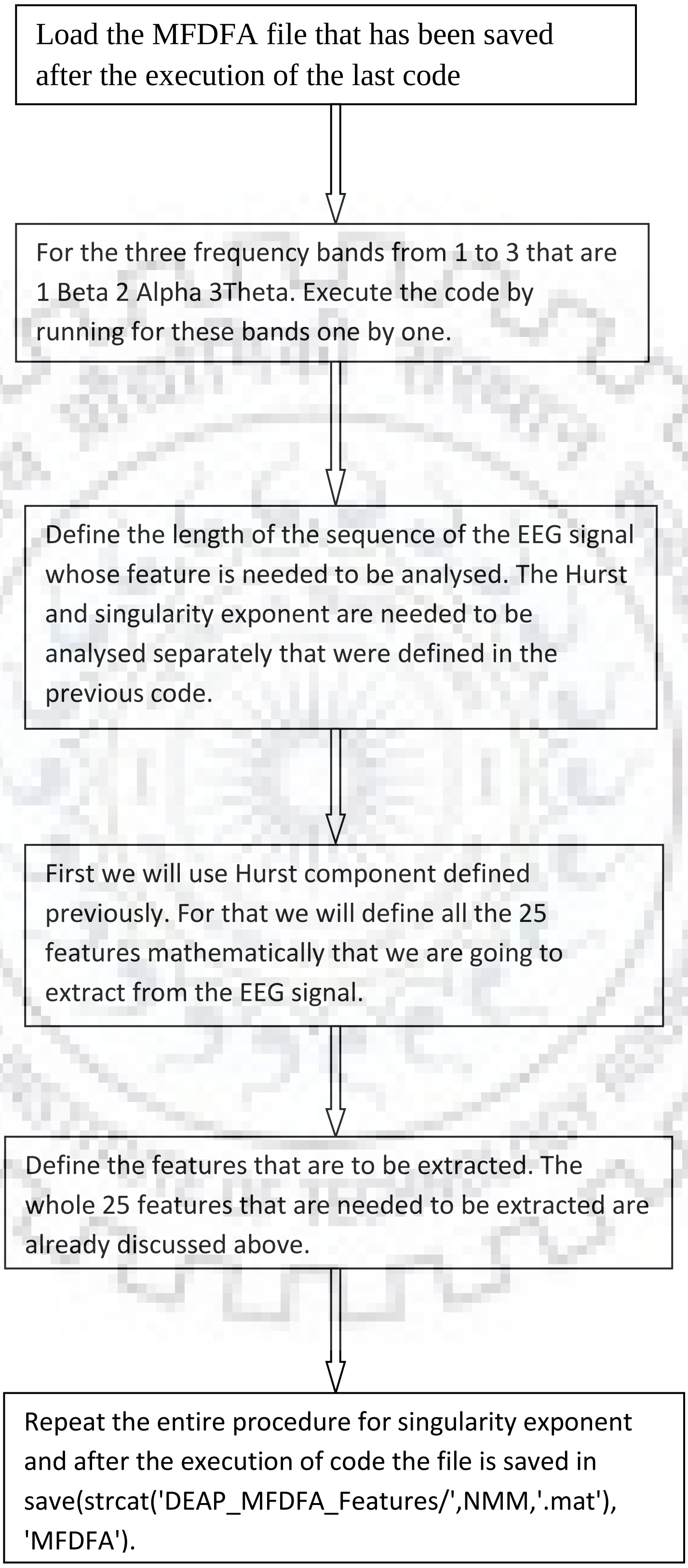


Figure 3.2: feature extraction in MATLAB

With the help of these features that we have extracted we can generate the bar graph plot and error plot. For that purpose we have to understand what results or parameters we have obtained after the feature extraction of the EEG signal. As earlier stated that we have done our analysis on 3 frequency bands that are - 1) beta 2) alpha 3) theta.
so after the code is run by putting the MFDFA file which is generated after the completion of the first code. As we have stated earlier the MFDFA generates a 1*80 cell 40 for Hurst exponent and 40 for singularity exponent. After the completion of second code three 1*80 cells are generated and each cell further contains 3*1000 cells 3 again for the frequency bands and 1000 for 25 features multiplied by 40 samples giving total 1000 features.

Features will give us the idea about how the cognitive activity is going to be while expressing a certain emotion while watching any particular video. We can quantize the cognitive activity using emotional classification or emotion enabling schemes which we will be discussing in the next chapter.

Chapter 4 Emotional classification

4.1. Emotion enabling schemes

The emotion class which is associated with the DEAP data set is majorly described on 2-D arousal-variance model used for emotional depiction. In general, class associated in each trial is described using 2 scales, namely the valance scale and arousal scale. Therefore depending n how many scales are used for depicting an emotion, and no of intervals defined various labelling schemes can be made to label EEG signal for each trial. The developed schemes based on QTFD (quadratic time frequency domain) using DEAP data set is summarised below-

4.2. One dimensional two class labelling scheme (1D-2CLS)

In this scheme valance and arousal are used independently to define three classes for each scale. Using the arousal scale a trial is assigned to emotion class. Which are high arousal (HA), neutral class , low arousal (LA) depending on arousal class value lies in which interval. If the value is greater than 5 than it will lie in high arousal class and if the value is lesser than 5 than it lies in low arousal class and same can be considered for valance.

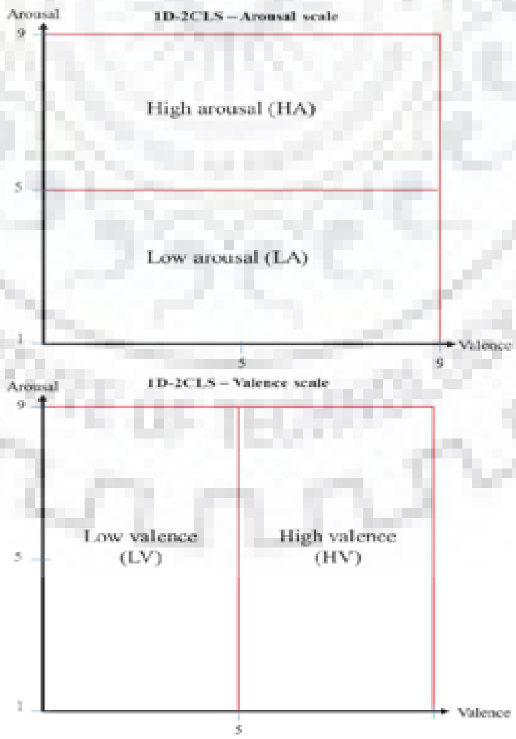


Figure 4.1: emotion labelling depicting 1D-2CLS. Above one is for arousal scale and lower one is for valance scale [25]

4.3. One-dimensional three-class labelling scheme (1D-3CLS)

“Following labelling scheme uses the arousal and valence scales independently to define three emotion classes for each scale. In general, using the arousal scale, a trial is assigned to the low arousal (LA) emotion class, the neutral emotion class or the high arousal (HA) emotion class depending on whether the associated arousal value is within the interval respectively. Similarly, the valence scale, a trial is assigned to the low valence (LV) emotion class, the neutral emotion class or the high valence (HV) emotion class depending on whether the concerned valence value is within the interval.”

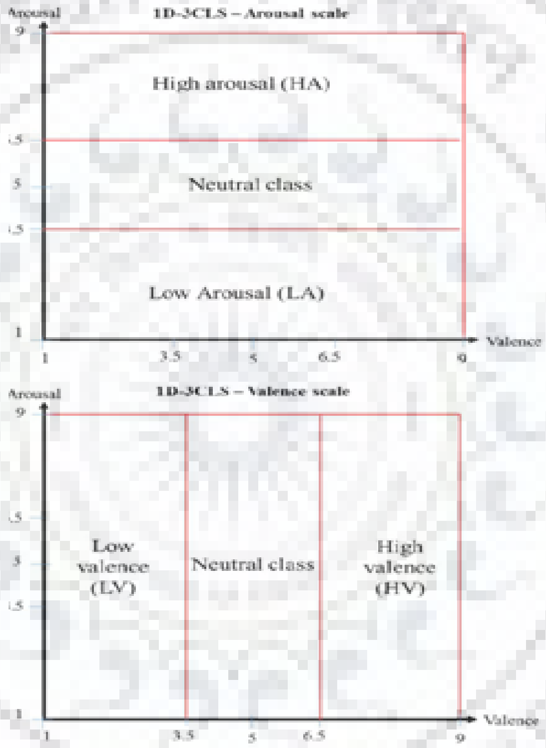


Figure 4.2: Emotion labelling depicting 1D-3CLS. Above one is for arousal scale and lower one is for valance scale. [25]

4.4: Two-dimensional four-class labelling scheme (2D-4CLS)

Following emotion labelling scheme uses the 2D arousal-valence plane, to depict various emotion states. In particular, using the 2D arousal-valence plane, an emotion state can be seen as a point in the 2D plane scaled by the axes of the valence scale and the arousal scale, such that the arousal and valence scales are represented by the vertical and horizontal axes, of the 2D plane. Therefore, the 2D arousal-valence plane can be divided into four quadrants, where each quadrant represents a particular emotion class. The emotion classes defined based on the 2D-4CLS are: the low arousal high valence (LAHV), high arousal high valence (HAHV), High arousal low valence (HALV) and low arousal low valence (LALV) emotion classes. The term high in each of the four defined emotion classes indicates that the arousal value or the valence value is more than five, while the term low indicates that the arousal value or the valence value is less than five.

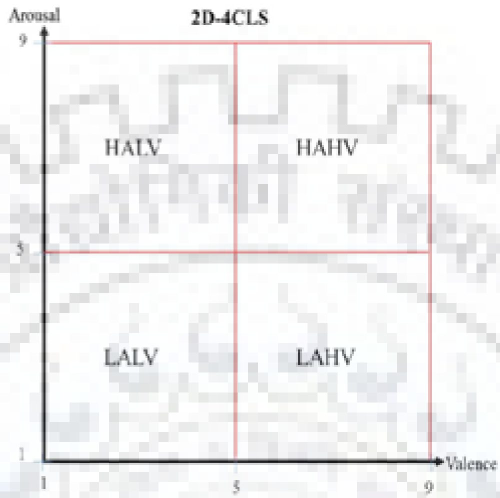


Figure 4.3: 2D-4CLS emotional enabling scheme. [25]

4.5. Two-dimensional five-class labelling scheme (2D-5CLS)

Following labelling scheme, expands the 2D-4CLS to include the neutral emotion class, which depicts the non-emotion state. In general, a division between the 2D arousal-valence plane into five regions, where each region represents a specific emotion class. The emotion classes defined based on the 2D-5CLS are: the LAHV, LALV, HALV, HAHV and neutral emotion classes. The neutral emotion class is used to represent the trials in which the arousal and valence value falls.

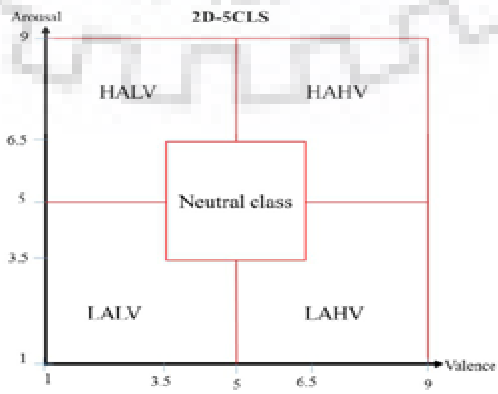


Figure 4.4: 2D-5CLS emotional enabling scheme. [25]

4.6. Evaluation analysis

In order to evaluate performance in recognising different emotional classes, three performance analysis techniques have been developed-

4.6.1. Analysis based on channel selected

In this technique the effects of using various sets of EEG channels which span distinct regions of the brain are investigated. Based on 4 emotion enabling schemes, the emotion classes are defined by recognising their accuracy. According to study the regions of brain that are involved in emotion responses are- prefrontal, frontal, temporal, occipital, parietal.

For implementation of the following analysis technique, an SVM classifier is to built which does the analysis associated with the emotion enabling schemes based upon the features extracted from each EEG signal in each setting of channels.

4.6.2. Analysis based on features

In this technique we try to find out that what effects would there be if the dimensionality of the extracted features are reduced. The MRMR (minimum redundancy maximum relevance) algorithm is used. Following algorithm uses the technique to select a feature subset that has maximum correlation with specific emotion class and minimum correlation between the selected features. This is helpful in studying the effect of feature utilization obtained using feature selection on accuracy of emotion enabling techniques. For the purpose of evaluation MRMR is applied on channel based evaluation on feature based vectors extracted from EEG channels associated with EEG signal to give the best results.

4.6.3. Neutral class exclusion analysis:

Following evaluation analysis, define the effect of inculcating the samples that correspond to the neutral class, which are defined in the 1D-3CLS and 2D-5CLS, on the accuracy of the remaining non-neutral emotion classes. Emotion states are written in a circular configuration around the circumference of the 2D arousal-valence plane. This implies that the region corresponding to the neutral class, does not describe emotional states effectively. Hence, in this analysis, we leave the features extracted from the trials that are falling within the region that represents the neutral class on the 2D arousal-valence plane. To use this evaluation analysis, we again perform the last two evaluation analyses, namely the channel- and feature-based analyses, after leaving the feature vectors that belong to the neutral class.

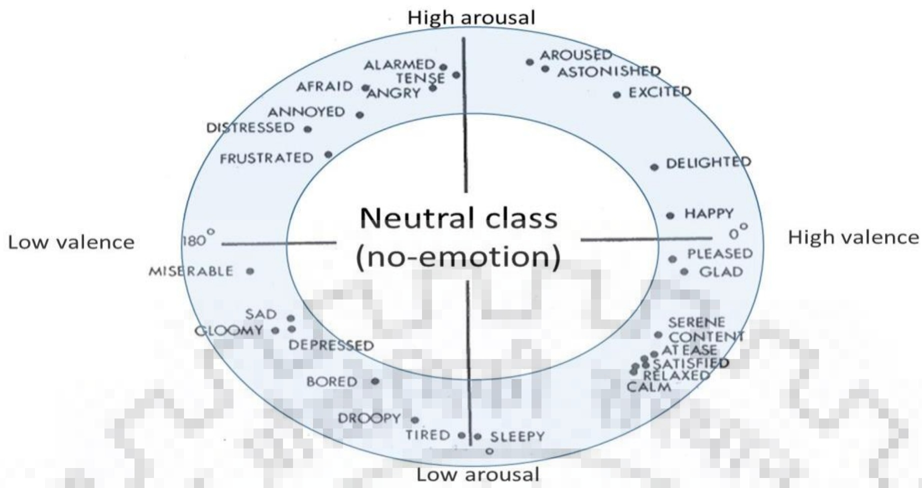


Figure 4.5: Emotion depiction on 2-D valence arousal plane [25]

We have used the MRMR (minimum redundancy maximum relevance) [14] algorithm to determine the valance and arousal. The values of these quantities will be discussed in the next section along with the conclusion.

Chapter 5: Results conclusion and future scope

5.1. Results

After the completion of 2 codes the bar plot and error plot are generated for different cases the parameters which will decide these plots are listed below-

1. The frequency band that are 1 beta 2 alpha 3theta
2. The exponent that you select that are 1 Hurst 2 singularity
3. The EEG channel you choose from 1-32
4. The sample you choose from 1-40
5. Videos you choose for comparing (minimum 2 to maximum 6)

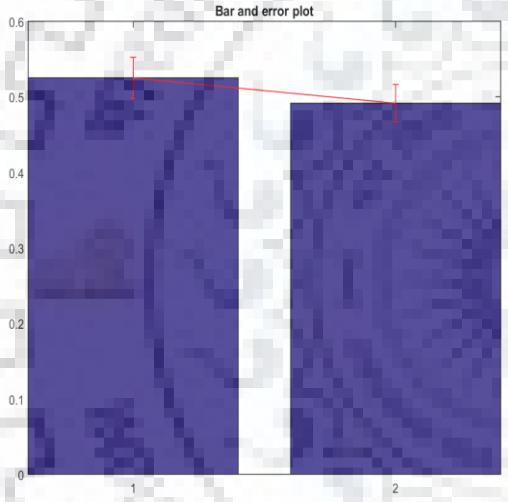


Figure 5.1: bar and error plot 1

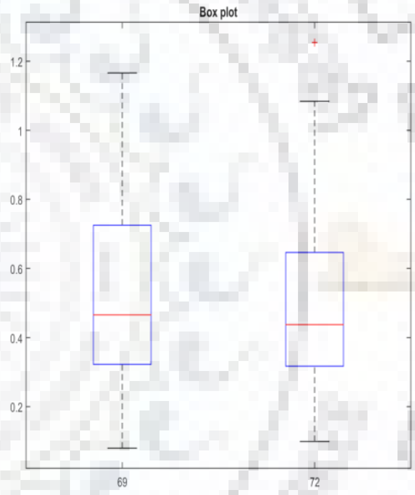
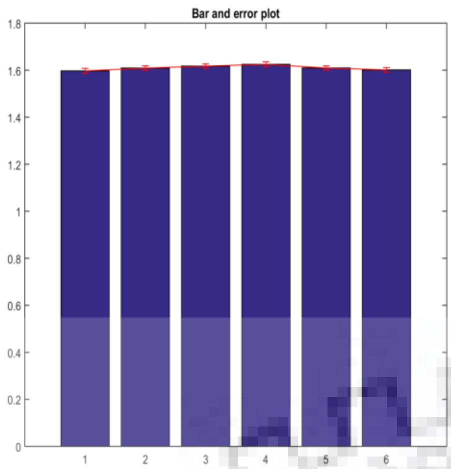


Figure 5.2: box plot 1

These plots are generated for theta frequency band used is Theta , the compared samples are 29 and 32, the exponent calculated is singularity exponent, channel no is 5, feature no is 4. As we can see from this figure that when 2 samples are there than the co-variance is relatively higher.



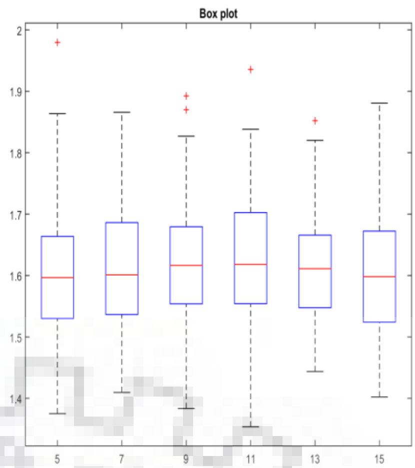


Figure 5.3: bar and error plot 2 Figure 5.4: box plot 2

These plots are generated for frequency band alpha, the compared samples here are 5,7,9,11,13,15, the exponent calculated is Hurst exponent, channel no is 5, and feature no is 6. As we can see as the no of samples is increased the co-variance decreases and co-relation increases.

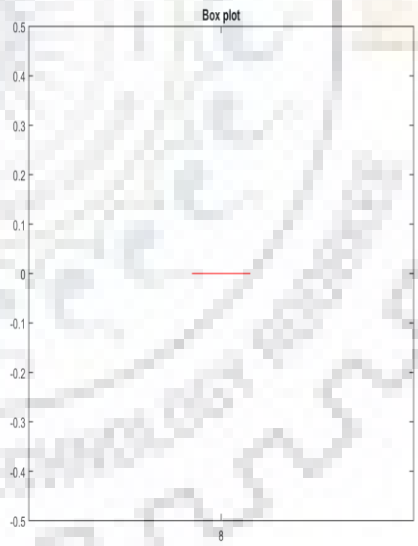


Figure 5.5: bar and error plot 3 Figure 5.6: box plot 3

In this case we have chosen alpha band, videos compared to each other are 1 and 8, we have chosen the Hurst component, channel no is 24 and feature selected is 22 as we can see that they exhibit entirely same characteristic for this feature thus these 2 video samples have entirely co-relevance with respect to each other and zero co-variance.

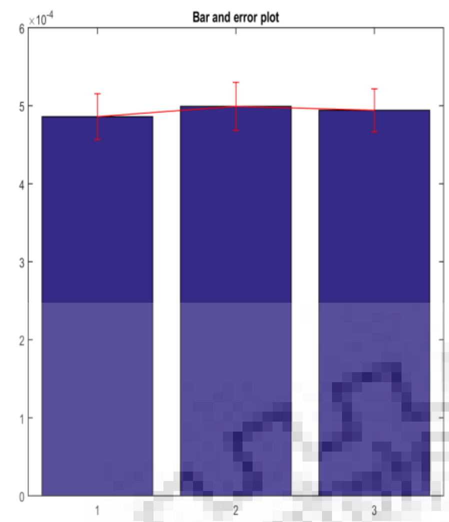


Figure 5.7: bar and error plot 4

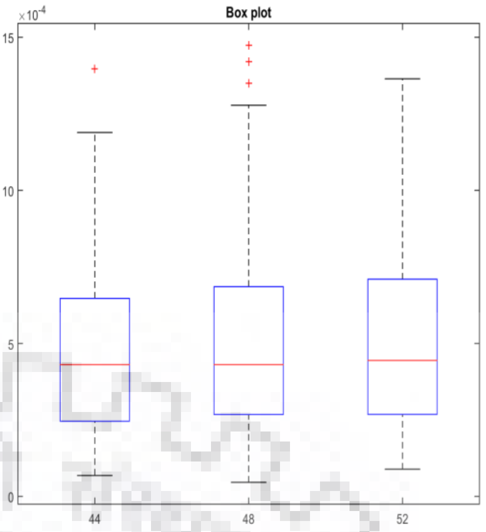


Figure 5.8: box plot 4

For this result also feature no 24 was selected so we conclude that as the feature no increases the magnitude of variance decreases. The band used here is beta, channel no is 7, exponent used is Hurst, samples compared are 4,8 and 12.

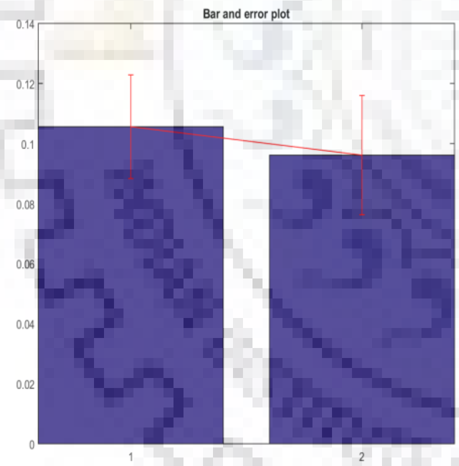


Figure 5.9: bar and error plot 5

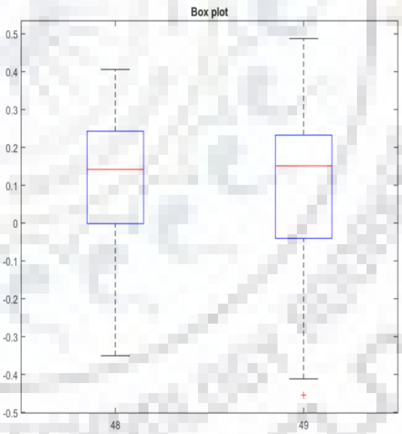
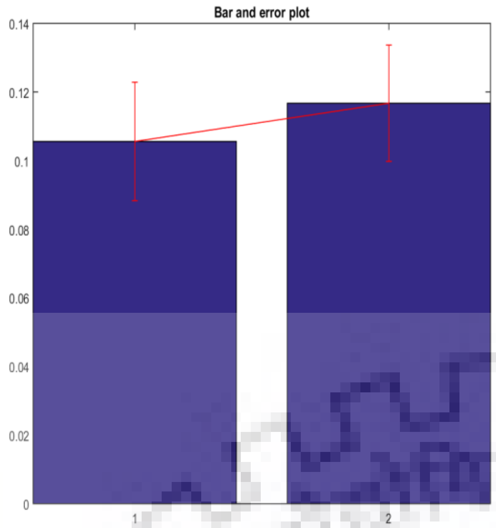


Figure 5.10: box plot 5

For this result also feature no 4 was selected so we conclude that as the feature no increases the magnitude of variance decreases. The band used here is beta, channel no is 3, exponent used is Hurst, samples compared are1 and 2.



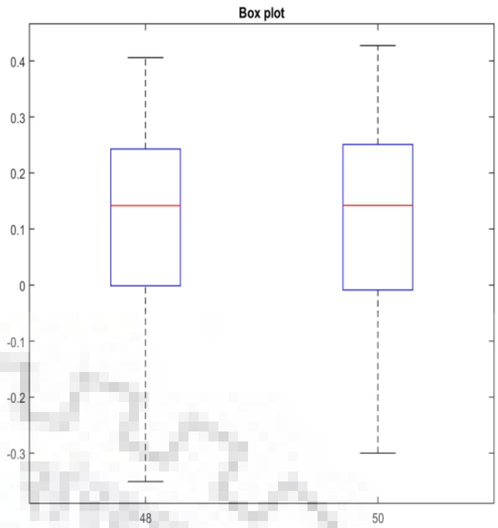
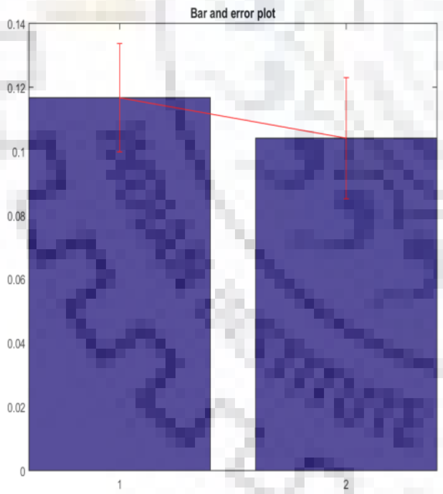


Figure 5.11: Bar and error plot 6

Figure 5.12: box plot 12

For this result also feature no 6 was selected so we conclude that as the feature no increases the magnitude of variance decreases. The band used here is theta , channel no is 3, exponent used is singularity, samples compared are 3 and 4.



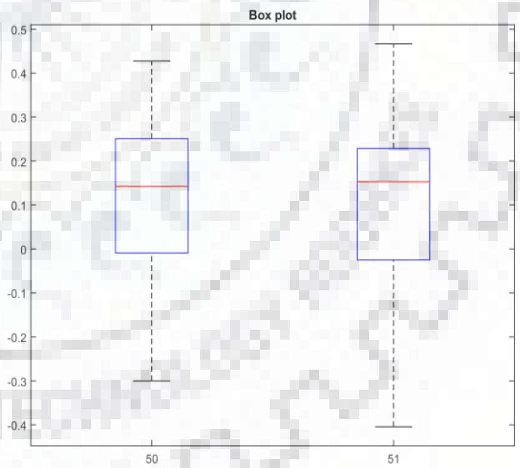


Figure 5.13: bar and error plot 7

Figure 5.14: box plot 7

For this result also feature no 8 was selected so we conclude that as the feature no increases the magnitude of variance decreases. The band used here is alpha, channel no is 10, exponent used is singularity, samples compared are 5 and 6.

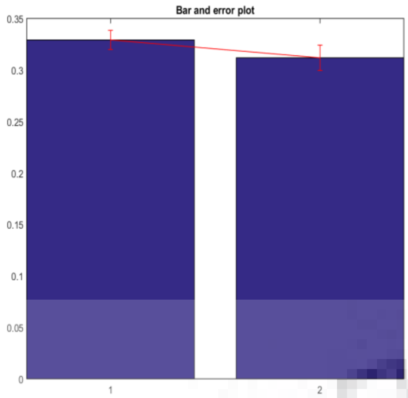


Figure 5.15: bar and error plot 8

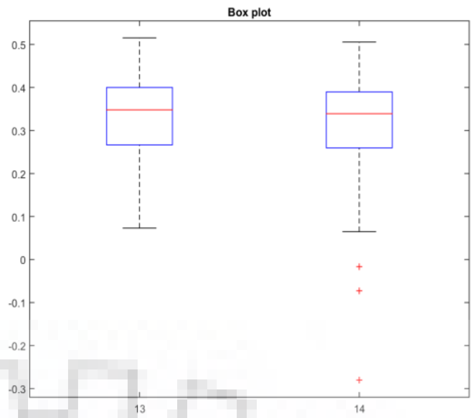


Figure 5.16: box plot 8

For this result also feature no 9 was selected so we conclude that as the feature no increases the magnitude of variance decreases. The band used here is theta, channel no is 10, exponent used is singularity, samples compared are 7 and 8.

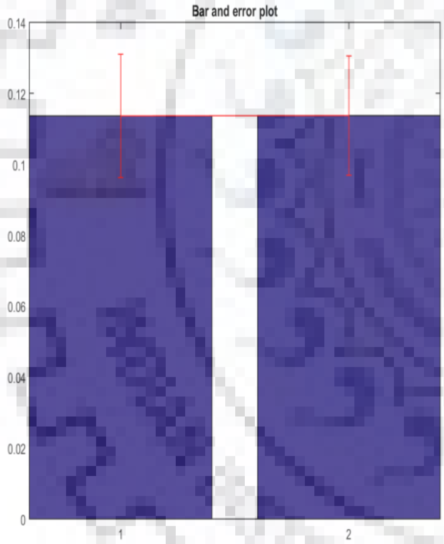


Figure 5.17: bar and error plot 9

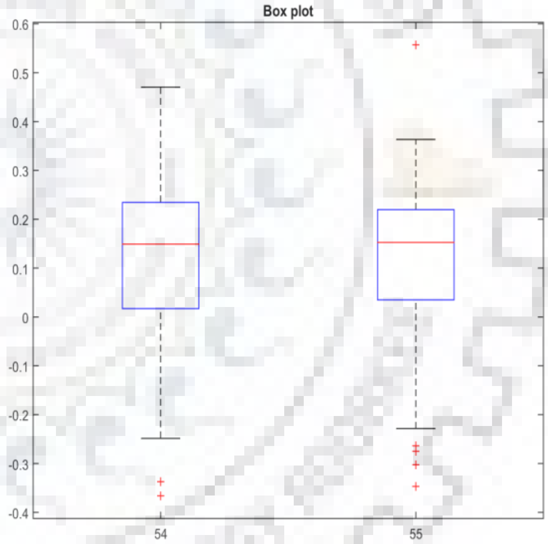
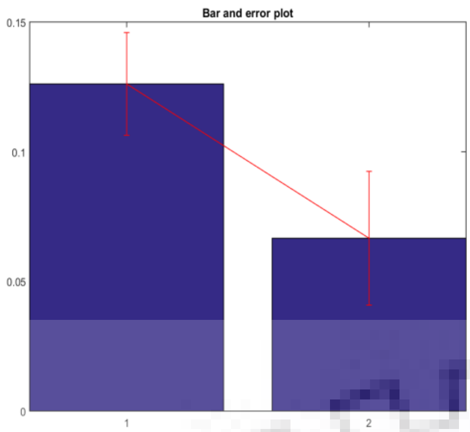


Figure 5.18: box plot 9

For this result also feature no 9 was selected so we conclude that as the feature no increases the magnitude of variance decreases. The band used here is beta, channel no is 13, exponent used is singularity, samples compared are 9 and 10.



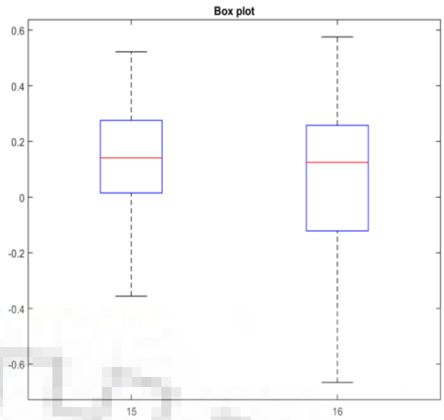
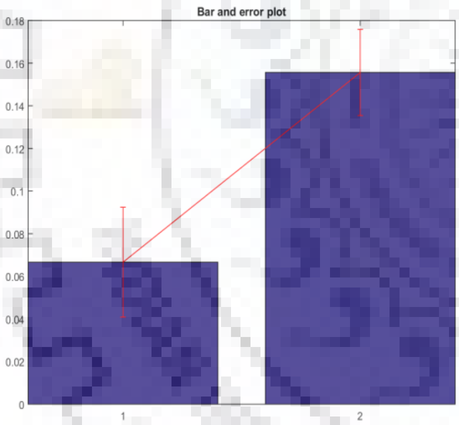


Figure 5.19: bar and error plot 10 Figure 5.20: Box plot 10

For this result also feature no 2 was selected so we conclude that as the feature no increases the magnitude of variance decreases. The band used here is theta , channel no is 3, exponent used is singularity, samples compared are 11 and 12.



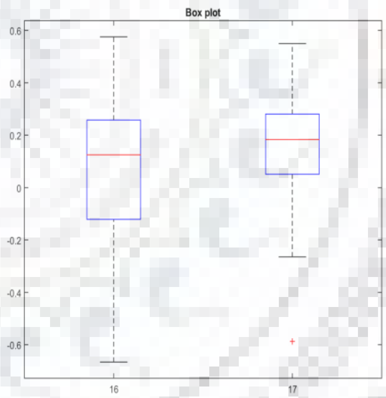


Figure 5.20: bar and error plot 10 Figure 5.20: box plot 10

For this result also feature no 10 was selected so we conclude that as the feature no increases the magnitude of variance decreases. The band used here is alpha , channel no is 12, exponent used is Hurst , samples compared are 13 and 14.

Hence now using these features we can classify in which range the emotions displayed while watching these video in the form of valance-arousal plane

As already discussed we have used MRMR algorithm for this and the results obtained from that is as follows

Online_id	Emotion displayed	AVG_Valence	Q1_Valence	Q2_Valence	Q3_Valence
1	Fun	6.8571	4	6.5	8
2	Exciting	5.9286	6	6	7.1667
3	Joy	6.9333	6	7	9
4	Fun	7	5	7	8.8333
5	Exciting	7.2	7	7	9
6	Fun	6.1333	5.1667	6	7
7	Pleasure	6.6667	6	7	8.6667
8	Angry	7.2667	5	7	8.8333
9	Sad	7.0667	6	7	8
10	Anger	5.8667	6	6	8.5
11	Happy	7.1429	3	7.5	8
12	Cheerful	5.9286	2	6	7
13	Love	6.5714	1.9167	7	8
14	Happy	7.0667	3	7	8.8333
15	Lovely	6.4667	2.1667	7	7.8333
16	sentimental	5.1333	1	5	6
17	Relaxing	6.0667	2	6	7
18	Sad	7.1333	2.1667	7	8
19	Joy	7.5333	3.1667	8	8
20	Love	6.2667	3	6	6.8333
21	depressing	4.1429	3	4	5
22	sentimental	4.2	2	4	5
23	melancholy	3.3333	3.1667	3	4
24	Sad	3.3333	2	3	4.8333
25	depressing	4.2	3	4	6
26	Mellow	4.2	2	4	4.8333
27	Sorrow	4.3333	2	5	5.8333
28	Sad	3.25	1.4167	3	4
29	Sad	3.4375	2	3.5	4
30	Boring	3.2	2	3	4
31	Terrible	3.6667	4.1667	3	5
32	Shock	4.6667	6.1667	5	5

Table 5.1: Emotion displayed by each video and the valance value. The valance value is calculated by 3 trials taking top 25% features, top 50% features and top 75% features.

Online_id	Emotion displayed	AVG_Arousal	Q1_Arousal	Q2_Arousal	Q3_Arousal
1	Fun	5.8571	4	7	7
2	Exciting	6.9286	6	7.5	8
3	Joy	6.4667	6	7	7
4	Fun	5.9333	5	6	7
5	Exciting	7.3333	7	7	9
6	Fun	6.2	5.1667	6	7
7	Pleasure	6.4667	6	7	8
8	Angry	6.0667	5	6	7
9	Sad	6.4	6	7	7.8333
10	Anger	7.0667	6	7	8
11	Happy	4.8571	3	5	6
12	Cheerful	3.3571	2	3	4.0833
13	Love	4.2143	1.9167	4	6.0833
14	Happy	4.7333	3	5	6.8333
15	Lovely	4	2.1667	4	6
16	sentimental	2.4	1	2	3
17	Relaxing	3	2	3	3.8333
18	Sad	3.8667	2.1667	4	5
19	Joy	4.4667	3.1667	5	5.8333
20	Love	4.1333	3	5	5.8333
21	depressing	4.2143	3	4.5	5.0833
22	sentimental	3.7333	2	4	5
23	melancholy	4.4667	3.1667	4	6
24	Sad	2.9333	2	3	3.8333
25	depressing	3.6	3	4	4.8333
26	Mellow	3	2	3	4
27	Sorrow	3.1333	2	2	5
28	Sad	2.75	1.4167	3	3.5833
29	Sad	3.625	2	3.5	5.5833
30	Boring	3.6667	2	3	4.8333
31	Terrible	5.4667	4.1667	5	7
32	Shock	6.4	6.1667	7	7

Table 5.2: emotion displayed by each video and the arousal value. The arousal value is calculated by 3 trials taking top 25% features, top 50% features and top 75% features.

Hence from the following data we can find the range of valance and arousal for different set of emotions. But it is very difficult to make conclusion for so many emotions so we have classified all the emotions into four major sets so that classification become easy and then the range of valance and arousal can be specified.

Emotion	Valance range	Arousal range
Sad	3.33-4.4	2.1-3.167
Joy	5.92-7.14	4-7
Anger	4.167-6.167	5-6
Shock	3.67-4.67	4.16-6.16

Table 5.3:Range of valance and arousal for different sets of emotions.

5.2 Conclusions

In conclusion we can say that the features that we have extracted display the cognitive activity of the brain for that particular emotion being displayed while watching that particular video sample. For different sets of features different co-variance and co-dependence is displayed which can be verified using the bar and error plots and box plots. The higher the value in bar plot more relevant is that feature for that particular video.

Secondly using the MRMR algorithm we are able to obtain the values of valance and arousal through which we can identify what emotion is being displayed. These valance and arousal values can be used in psychometric analysis of a person and can be sued in clinical diagnosis of brain if a person is feeling some sort of emotional distress. Hence the cognitive activity of brain can be measured.

Thus we can say that emotional activity is a good method to measure the cognitive activity of the brain through which can depict the brain’s activity mathematically as well as graphically to find out the working of brain using EEG signal analysis.

5.3. **Future scope**

- In the coming time the psychometric analysis can be used to cure neuro-diseases by predetermining the emotional imbalance pr anxiety levels in the patients.
- Using these emotional analysis techniques we can find out the behaviour of a person in a particular situation.
- In future more advance techniques to show the actual thoughts of a person using these analysis can be developed.
- Better feature extraction techniques will help doing better analysis and clearer emotion display.
- Emotional classification can be made more complex for complex emotions which consists mix of 2 or more emotions.

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