

# Emotion Detection based on Electroencephalography (EEG)

Minakshi S. Panchal

M.Tech Scholar, Dept. of Electronics and Telecommunication Engineering, Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra- India (402103).

\*\*\*

**Abstract** - Since last few years, many researchers are interested in Brain Computer Interface (BCI). Emotions are the integral part of the human being. An emotion reflects the inner activities of the human brain. In this paper emotions are detected by the Electroencephalography (EEG) method. Electroencephalography (EEG) signals use to record and analyze brain signals using different electrodes. Advantages of EEG methodology are its non-invasive, good temporal resolution, cost effective and easy to handle. In proposing method online available DEAP database is used for emotion detection in 4 classes (Happy, Angry, Sad, and Relax). DEAP database consist pre-processed EEG data. Features are extracted in 4 frequency bands such as delta, alpha, beta and theta using discrete wavelet transforms (DWT). Power spectral density (PSD), average band power is calculated in frequency domain feature. Time domain features also calculated such as mean, root mean square, variance, standard deviation, kurtosis, skewness. According to this valence and arousal values are calculated. By comparing valence and arousal values, emotions are detected. Happy emotion represents class 1, angry emotion represent class2, sad emotion represent class3, and relax emotion represent class4. The accuracy rate for class1 is 73%, class2 is 83%, class3 is 77% and class4 is 75% respectively.

available DEAP database is used. The data is in the form pre-processed data, features are extracted in time and frequency domain. An algorithm is developed to identify emotional states based on 2D dimensional model for the available database. This paper arranged such as introduction is in section 1, section 2 is the literature review. Methodology and results discussed in section 3 and 4. Conclusion section in section 5.

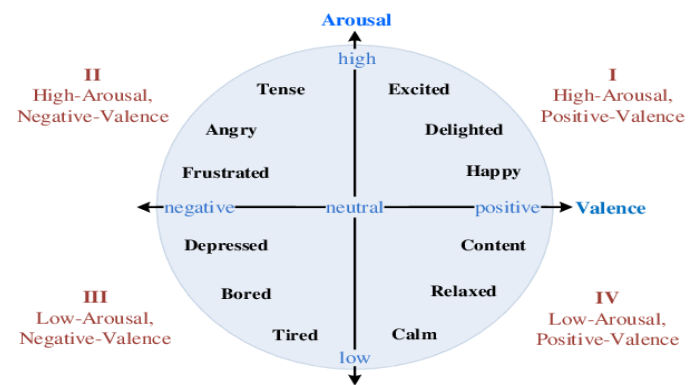


Fig -1: Dimensional Model

**Key Words:** Brain Computer Interface, Electroencephalography, DEAP, Discrete Wavelet Transform, Power spectral density.

## 1. INTRODUCTION

From last few years brain computer interfaces (BCI) is growing research field. It analyzes and records the signals from the brain. It consists both physical and physiological signals. Now real time signals are used to detect the emotions. Applications of BCI are epilepsy detection and emotion detection. [3] Emotion detection is the growing field in which it makes breeze between human being and computer. There are many devices used to capture EEG signals. Emotions reflect the inner state if human being. For example, under graduate students face lot problems due to pressure of college, due to age and about the future. The experimentation is undertaken to detect the state of inner emotion on the EEG signal. The outcome of the studies undertaken is promising. Emotional intelligence is an important aspect of the balanced personal and professional life. Hence, researchers are keenly interested in analyzing emotions in a systematic manner. This paper gives the overview of emotion detection based on EEG signals. Online

## 2. LIERATURE SURVEY

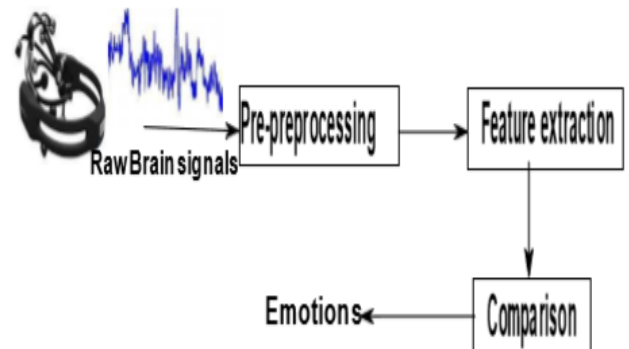
There are many researchers used DEAP dataset for emotion detection. [2], gives the information about emotion detection using multiple numbers of channels Electroencephalography (EEG) signals with different frequency bands. Accuracy of the gamma frequency band was 95%, according to the number of channels were increased, accuracy also increased. [1], DEAP and SEED-IV both databases used for emotion detection. Features extracted are band energy, differential entropy, Hjorth features in time domain and other features also extracted. [5], for frequency, statistical and nonlinear dynamic features accuracy of arousal were 80.72% and 83.78% for valence using MCF. [7], proposed a method based on Functional Near Infrared Spectroscopy (FNIRS) and Electroencephalography (EEG) to detect emotion by multimodalities and spatiotemporal data with neural signal traits. In this method webcam was used to capture facial expressions. [8], used LSTM Recurrent Neural Network, calculate average accuracy 87.99%, 85.45% and 85.65% for liking, valence and arousal class.

From the above survey, it is view that many authors have developed different algorithms using various features. In this method features is extracted in time and frequency domain. According to that valence and arousal values are calculated

to detect the emotions and classify into 4 classes for online available DEAP database. Following Table -1 show the different research paper used for the proposed method.

**Table -1:** List of papers with different methods

Author	Title	Year	Method
Yanjia Sun, Husan Ayaz, Ali N. Akansu [5].	Emotion Recognition Based on EEG using LSTM Recurrent Neural Network	2015	EEG and FNIRS both signals used
Anita Patil, Chinmayee Deshmukh, Dr. A. R. Panat [9].	Physiological Construction in the occ model of emotion	2016	Hajorth and higher order crossing used
N. Jadhav, Y. Joshi, R. Manthalkar [10].	Effect of meditation on emotional response: An EEG based study	2017	Image processing
Thejaswini S., K.M. Ravikumar, Jhenkar L., Aditya Natraj, Abhay K. K. [1].	Analysis of EEG based Emotion Detection of DEAP and SEED-IV Databases using SVM	2019	SEED-IV and DEAP dataset used



**Fig -2:** Proposed Methodology

### 3. METHODOLOGY

From the above survey, it is observed that supervised algorithm developed for emotion detection. The online DEAP database is used. To detect emotion using EEG signals many intermediate steps are to be performed: data acquisition, pre-processing or artifact filtering, feature extraction and comparison. The methodology for the research work is discussed below in Fig -2

#### 3.1 Data Acquisition

In the proposed method, pre-process DEAP EEG database is used and it is online available. The Data acquisition method consists raw EEG data and event separation of EEG data. Raw EEG data contain EEG data and peripheral physiological data. EEG and peripheral physiological data of 32 participants, who are 16 women and 16 men, between the ages of 19 to 37. This data have been recorded using 32 EEG electrodes and 8 physiological electrodes. The EEG Device having sampling rate of 500Hz. Each participant watched 40 music videos and the length of the music video is 1 minute long. The participant self assessment manikin (SAM) rating of valence and arousal values of 40 music video is also available. DEAP Data for EEG is obtainable in array shape of 40 (video/trail) x 40 (32 EEG electrodes and 8 peripheral electrodes) x 8064 (data samples). Also event separation is done for music video based on length of video.

#### 3.2 Pre-processing

In this proposed method pre-processed EEG data are used. To remove the noise from the raw data, signals are passed through 3 different filters. These are notch filter, 1D 10<sup>th</sup> order median filter and band pass filter of order 20. Notch filter of 50 Hz/60Hz used to remove line frequency artifact from giving raw signals. Impulsive noise is removed from the present data by 1D 10<sup>th</sup> order median filter. Last band pass filter of order 20 used. Upper and lower cutoff frequencies are 60 and 0.1.

#### 3.3 Feature Extraction

In this process pre-process data are passed to extract meaningful features. From EEG signals various features can be extracted. In this paper time domain and frequency domain features are calculated. To obtain 4 frequency bands such as alpha, beta, delta, theta Discrete Wavelet Transform (DWT) is used. For this 4 bands average power is determined. Filtered data on EEG signal's power spectral

density are finding out for each emotion. Power spectral density (PSD) in the form of Welch PSD and periodogram PSD is calculated. There are many features extracted in time domain, such as mean, root mean square, variance, standard deviation, skewness and kurtosis using inbuilt functions in MATLAB.

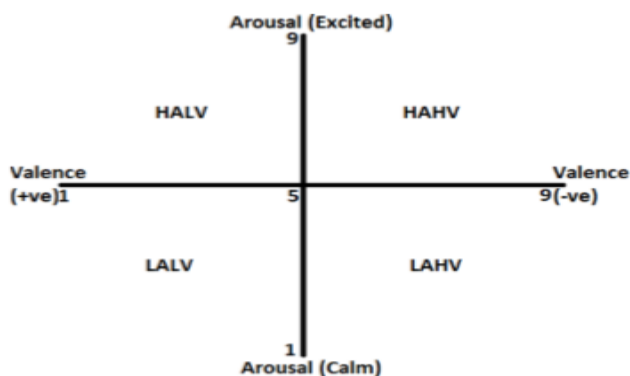
Following table shows the extracted features for this methodology.

**Table -2:** Extracted Features

Feature Type	Feature Name
Time Domain(Statistical Features)	Mean, Root Mean Square, Standard Deviation, Variance, Skewness, Kurtosis
Frequency Domain Features	Power Spectral Density, Average Band Power

### 3.4 Comparison

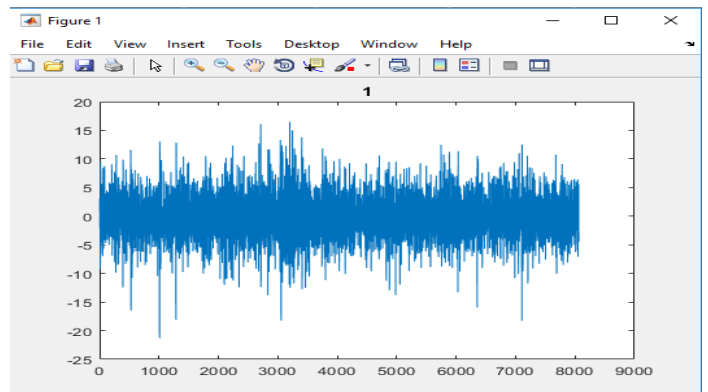
After extracting necessary features from the input signals, it is easy to examine valence and arousal values. From these values, emotions are classified into 4 classes. According to 2D Russells plane, scale of arousal from excited to calm and negative to positive for valence. Both valence and arousal ranges from 1 to 9. For arousal excited (high) value is a scale from more than 5 to 9 and calm (low) value is a scale from 1 to less than 5. For valence, range of negative is less than 5 and range of positive is more than 5. Based on these values, Happy emotion represent class1, Angry emotion represent class2, Sad emotion represent class3 and Relax emotion represent class4.



**Fig -3:** 2D Russells plane

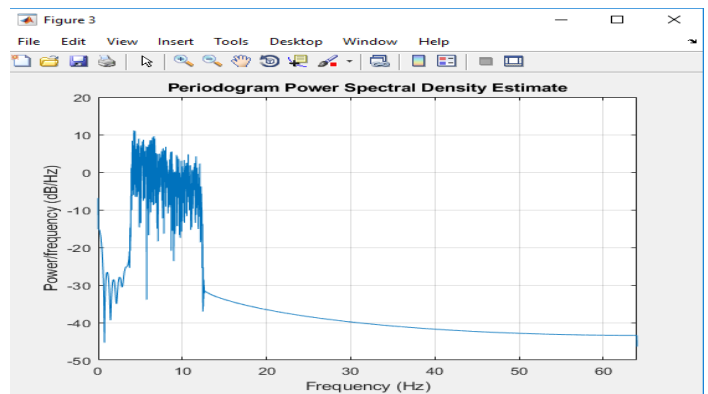
### 4. RESULTS

Fig -4 Shows the Raw EEG signal of 8064 data samples acquired from DEAP database.

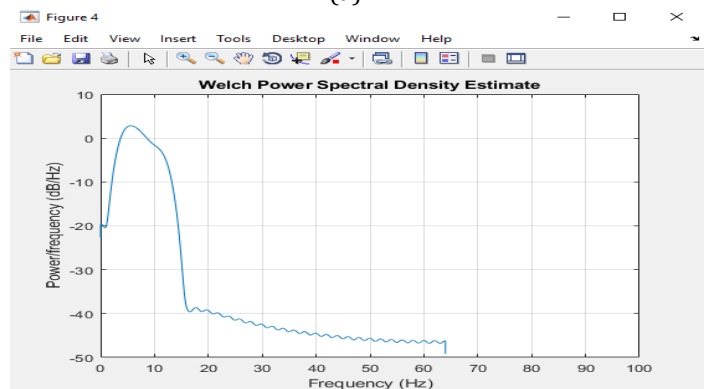


**Fig -4:** Raw EEG Data

Fig -5(a) shows the periodogram PSD of filtered data for happy emotion and Fig -5(b) shows the Welch PSD of filtered data for happy emotion.



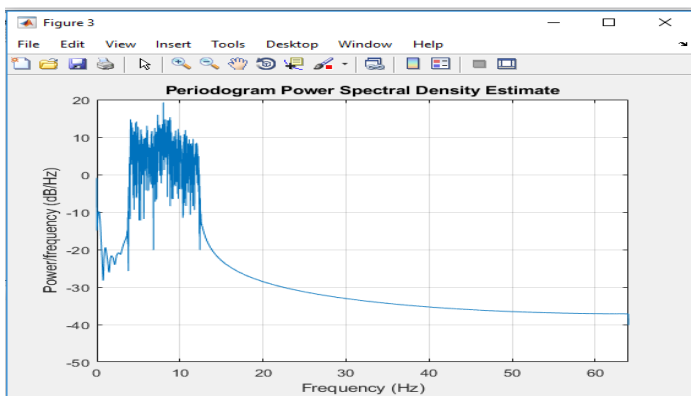
(a)



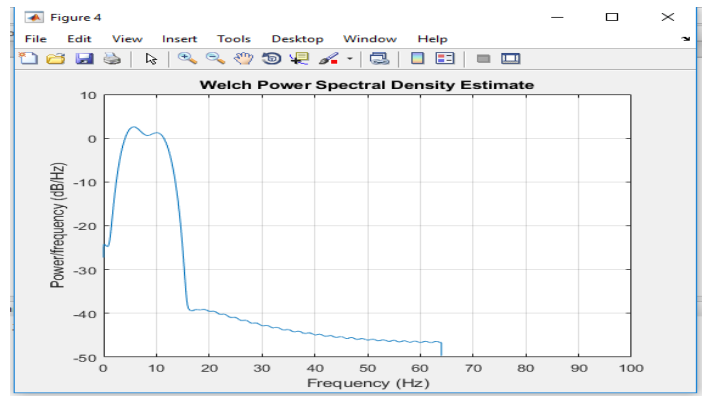
(b)

**Fig -5:** (a) periodogram PSD for Happy emotion(b) Welch PSD for Happy emotion

Fig -6(a) shows the Periodogram PSD of filtered data for angry emotion and Fig -6(b) shows the Welch PSD of filtered data for angry emotion.

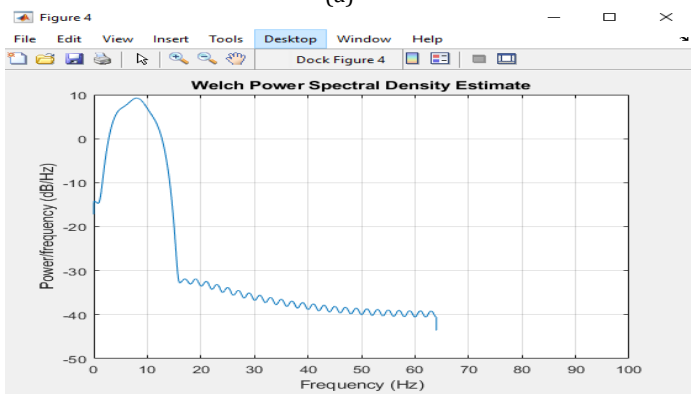


(a)



(b)

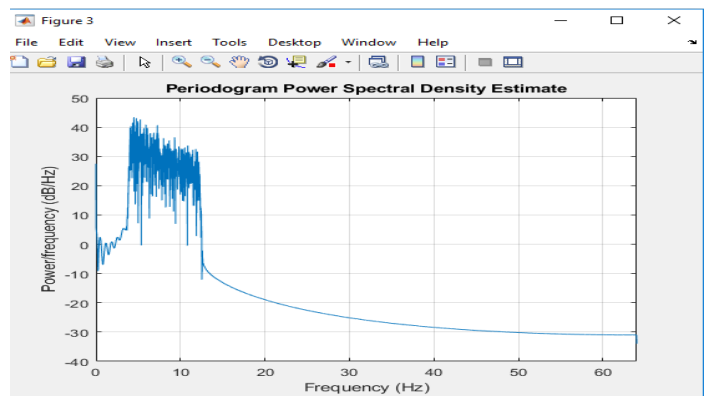
**Fig -7:** (a) Periodogram PSD for Sad emotion (b) Welch PSD for Sad emotion



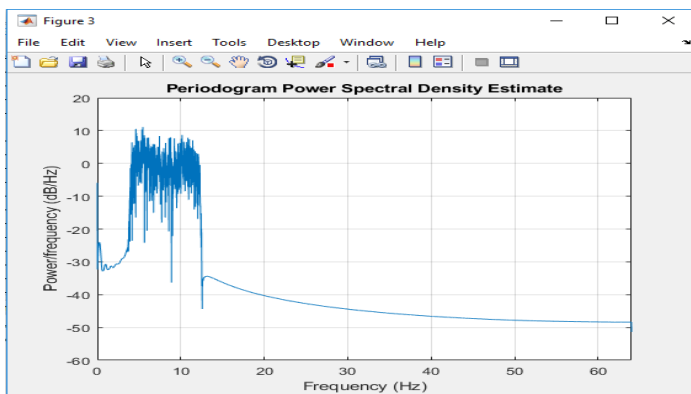
(b)

**Fig -6:** (a) Periodogram PSD for Angry emotion (b) Welch PSD for Angry emotion

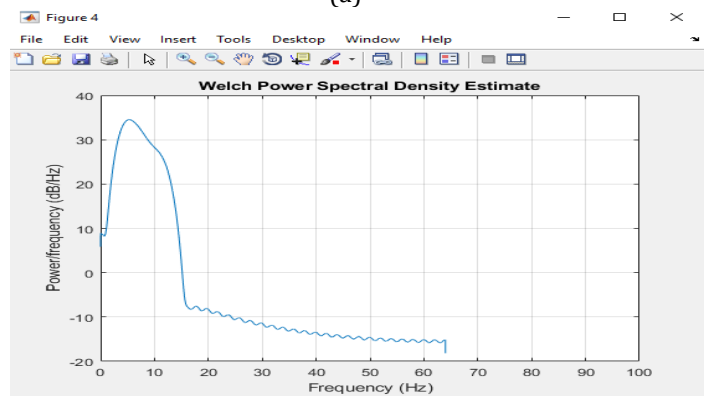
Fig -7(a) shows the periodogram PSD of filtered data for sad emotion and Fig -7(b) shows the Welch PSD of filtered data for sad emotion.



(a)



(a)



(b)

**Fig -8:** (a) Periodogram PSD for Relax emotion (b) Welch PSD for Relax emotion

Following Table shows the results of time domain features using various parameters.

**Table -3:** Results of Time Domain Features

	Emotion			
	Happy	Angry	Sad	Relax
Mean	0.0585	-0.1163	-0.0654	3.0648
Root Mean Square	3.2757	7.0169	3.4672	117.1911
Standard Deviation	3.2754	7.0164	3.4668	117.1586
Kurtosis	6.0831	4.2567	5.0161	14.6397
Skewness	0.0270	0.0337	-0.0436	-0.0034
Variance	2.5412	49.2300	12.0184	1.3726

Accuracy of detecting emotion using this method shown in below Table -4 and Table -5 shows the overall performance of this method compared with SEED-IV database.

**Table -4:** Accuracy Rate

Sr. No	Class	Accuracy Rate
1.	HAHV	73%
2.	HALV	83%
3.	LALV	77%
4.	LAHV	75%

**Table -5:** Overall Performance

Class	DEAP Data	SEED-IV Data
HAHV	73%	79%
HALV	83%	76%
LALV	77%	77%
LAHV	75%	74%

## 5. CONCLUSION

This paper, detects the human emotion such as Happy, Angry, Sad, and relax using the brain signals. The proposed method contains EEG signals. Features are extracted in time and frequency domain. An experimental result shows the PSD and time domain results. It gives the accuracy rate for each emotion. Accuracy of class1 (HAHV) 73%, class2 (HALV) 83%, class3 (LALV) 77% and class4 (LAHV) 75%. In future the exact method can be useful to detect emotion and facial expressions using real time signals.

## ACKNOWLEDGEMENT

I would like to thank my teachers for their ideas, expertise, time, encouragement and for providing useful material for completing this research paper.

I want to express my gratitude to my family and friends, who helped and encouraged me throughout my life.

## REFERENCES

- [1] S. Thejaswini ,K M Ravikumar, L. jhenkar , A. natraj,K .K abhay, "Analysis of EEG Based Emotion Detection of DEAP and SEED-IV Databases using SVM",International Journal of Recent Technology and engineering(IJRTE) ISSN:2277-3878, Volume-8, May 2019Issue-1C.
- [2] X. Liu, and S. Lu, "Emotion Recognition from Multichannel EEG Signals using K-Nearest Neighbor Classification." *Technology and Health Care Preprint* (2018): 1-11.
- [3] G. Molina, T. Tsoneva and A. Nichol, "Emotional Brain-Computer Interfaces", *IEEE*, 2009.
- [4] M. Kaur, "Technology Development for Unblessed People using BCI: A Survey", *International Journal of Computer Applications* (0975 – 8887) Volume 40, Feb. 2012.
- [5] Li, Xian, J. Yan, and J. Chen. "Channel Division Based Multiple Classifiers Fusion for Emotion Recognition using EEG Signals." In *ITM Web of Conferences*, EDP Sciences,vol. 11, 2017,p. 07006.
- [6] M. Hosny, Y. Al-Ohali, and A. Al- Wabil. "Review and Classification of Emotion Recognition Based on EEG Brain-Computer Interface System Research: A Systematic Review." *Applied Sciences* 7, no. 12 (2017): 1239.
- [7] Y. Sun, H. Ayaz, and A. N. Akansu, "Neural Correlates of Affective Context in Facial Expression Analysis: A Simultaneous EEG-FNIRS Study", *GlobalSIP, Symposlums on Signal Processing Challenges In Human Brain Connectomics, IEEE*,2015.
- [8] Alhagry, Salma, AlyAlyFahmy, and Reda A. El-Khoribi "Emotion Recognition based on EEG using LSTM Recurrent Neural Network",(*IJACSA*) *International Journal of Advanced Computer Science and Applications*, Vol. 8, No. 10, 2017, PP. 355 – 358.
- [9] G. Clore and A. Ortony. "Psychological construction in the occ model of emotion". *Emotion Review*, 2013,5(4):335–343.
- [10] N. Jadhav, Y. Joshi, R. Manthalkar, "Effect of meditation on emotional response: An EEG based study,"*Article in Biomedical Signal Processing and Control* Volume 34, Apr. 2017:101-113.