

Techniques Used In Automatic Emotion Recognition From EEG Signals: A Review

¹Elizabeth Paul, ²Asha Raj

¹PG Student, ²Assistant Professor

¹Computer Science and Engineering,

¹Rajagiri School of Engineering and Technology, Kochi, India

Abstract : Emotion recognition is an important area of research which is very much relevant in the modern world. It is the foundation of Brain Computer Interface(BCI) technology. Emotions can be reflected from speech, body language, voice indentation etc[1]. But automatic emotion detection from EEG signals are more reliable than conventional methods. Advantages of using emotion detection using EEG signals is that it works with non-cooperative and in accessible cases, less affected by non-emotion factors. Some of the challenges faced by emotion recognition from EEG signals are less number of electrodes are available for brain signal capturing and computational complexity. Emotion Recognition has various applications in medical field, robotics, customer satisfaction, criminal investigation etc. Techniques used in emotion recognition are signal processing, feature extraction and classifications. In this paper we are going to explain these techniques in detail.

IndexTerms - Brain Computer Interface(BCI), EEG Signals, Feature extraction, feature classification.

I. INTRODUCTION

Emotions play an important role in human cognition. BCI's currently available only focuses on artificial intelligence and not on emotional intelligence. If emotional intelligence is given to a robot it can perform more efficiently and accurately. Hence emotional recognition is an emerging research area in the modern era of automation. The conventional methods for emotion recognition are - facial expressions, voice indentations. These are not reliable in all cases. Automatic emotion recognition using EEG signals are more reliable because it is based on the physiological signals.

The signals which are related to emotions are Galvanic Skin Response (GSR) Electromyography(EMG) Heart Rate(HR) and Respiratory Rate(RR) .Electroencephalography (EEG), functional Magnetic Resonance Imaging (fMRI),or Positron Emission Tomography (PET) are functional neuro imaging techniques which can also be used for emotion recognition[2].Disadvantages of EEG signals are poor spatial resolution and requires many electrodes placed at various sites on the head. But it provides great time resolution, which allows researchers to study phase changes in response to emotional stimuli..EEG signals are fast and inexpensive which makes it preferred technique for emotion recognition. New wireless, portable EEG devices are available in market these days. It can be used for assisting psychologist or therapist, giving emotional intelligence to robot etc. There are some correlation between brain waves and emotions. Our brain consists of neurons, when they are active they produce electrical energy, which could be measured outside our skull, which is done in EEG .Brain neurons produce a rhythmic signals which is constantly present. PPIs where earlier found out by experimentally through Tandem affinity purification which is also known as tap tagging. It is a technology that is used for the identification of interactions and it involves creating fusion proteins with a designed piece the tap tag on the other end. Through several process like affinity selection and washing a native elution is produced, which consists of new proteins and its interacting partners which can be found out by mass spectrometry.

These signals are classified based on their frequency. Delta waves has a frequency of 3HZ which can be produced during our sleep. Beta waves has a frequency of 8 to 12 HZ,which is related to alert state of our mind. Alpha wave has a frequency of 4 to 7 HZ which is related to a relaxed person[2].In this paper we review various approaches used in emotion detection from EEG signals, that includes EEG signal collection and pre-processing, feature selection, feature extraction and calculations and finally the emotion classification techniques .

II. BACKGROUND KNOWLEDGE

2.1 Brain Waves

Our brain is made up of billions of cells called neurons. Waves which are formed when neurons communicate with each other is called brain waves. Speed of brain waves are measured in hertz. Based on the frequency brain waves are divided into Beta waves, Alpha waves, Theta waves, Delta waves and Gamma waves. Alpha waves comes within a frequency range of 8hz and 12hz. This waves are produced when we are at the state of mental relaxation or in the meditation state. Beta brainwave has a frequency range from 12hz to 27hz, beta waves are emitted when we are consciously alert or we feel agitated, tense and afraid. Lack of beta activity can cause mental or emotional disorders such as depression and insomnia.

Theta brain waves have a frequency range of 3hz to 8hz. These waves are produced when we are at light sleep or extreme relaxation. Delta waves are at a frequency range of 0.2hz-3hz. These waves are emitted when we are at deep and dreamless sleep. During this stage we are completely unconscious. Delta waves have the lowest frequency. Gamma waves are at a frequency range of 27hz and above. These waves are associated with language, idea formation and learning. These are the highest frequency waves. According to doctors, a person without any brain waves for 30 minutes is officially dead. Roboticists can use these brain waves to design mind control systems.

2.2 Emotion Models

Usually two models of emotions are widely used in emotion recognition research. First one is using word labels like happy sad surprise anger disgust fear etc., which is usually used in emotion recognition using facial expressions [4]. Other one is based on valence and arousal values that are widely used to detect emotions from EEG signals. There are two well-known spaces to discriminate various emotions, they are discrete classification space [5] which includes fewer emotions and dimensional space which provides more number of emotions [6]. Dimensional space with valence and arousal (V-A Space) is more popular for finding emotions. Valence is marked through X axis and arousal through Y axis. In the V-A space, the emotions are marked through Y axis in terms of active/non-active and X axis in terms of positive/negative along A and V axes respectively [7]. Four classes (high valence high arousal (HVHA), high valence low arousal (HVLA), low valence high arousal (LVHA), and low valence low arousal (LVLA),) are being considered in V-A space [8].

2.3 EEG Signals

A high number of neuro-psychological studies have reported correlations between EEG signals and emotions. There are two main areas of the brain correlated with emotional activity: the amygdala (located close to the hippocampus-, in the frontal portion of the temporal lobe); and the pre-frontal cortex (covers part of the frontal lobe). Amygdala's activation seems to be more related to negative emotions than positive ones. EEG is a medical imaging technique that reads electrical activity inside our brain. It measures voltage fluctuations inside our brain. Voltage measured from an Adult's scalp will be 10 - 100 micro volts [9]. These waves that are measured from the scalp are divided into alpha, beta, gamma, delta and theta waves based on its frequency values. Each waves are more prominent in different states of our mind. For example delta waves are associated with unconscious mind.

III. SIGNAL PREPROCESSING METHODS.

Signal pre-processing methods should be applied to signals which are recorded from human brain because it has poor special resolution. The portions of collected signals are coming from eyes, muscles and other external sources which contain noise signals. It has to be removed before emotion detection.

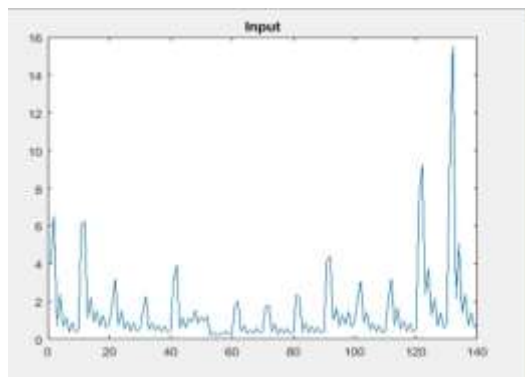


Figure 1. Input EEG Signal

3.1 Discrete Wavelet Transform

Discrete wavelength transform decomposes the signal into different approximation and different frequency ranges while conserving the time information of the signal. DWT is applied to signals for feature extraction. Energy and entropy are extracted from signals using DWT and using that we could calculate various features. Frequency domain gives more information than time domain, so it is important to convert signal from time domain to frequency domain using DWT[3]. A mother wavelet is used as basis, then mother wavelet is shifted and scaled. The original signal is the approximation of several scaled and shifted wave. In DWT scaling and shifting factor are selected as the powers of 2.

3.2 Continuous Wavelet Transform

A continuous wavelet transform (CWT) is used to divide a continuous-time function into wavelets. Unlike Fourier transform, the continuous wavelet transform holds the capacity to create time-frequency representation of a signal that deals very good time and frequency localization. It is applied on EEG signal to decompose the signal into different frequency

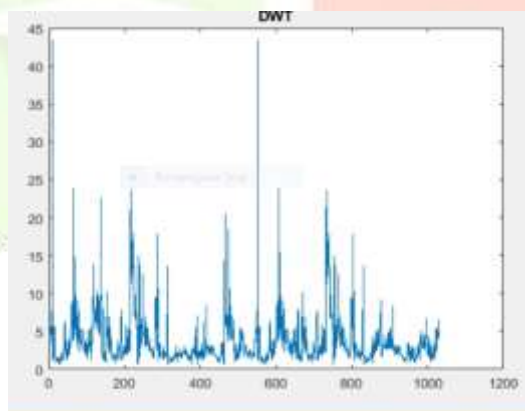


Figure 2. Discrete Wavelet Transform

bands. There are many features that are hidden inside EEG signals. EEG signals are measured in micro volts. So we need to do signal processing in order to extract features from EEG signals.

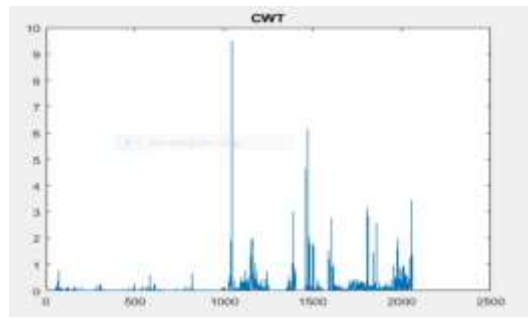


Figure 3. Continuous Wavelet Transform

3.3 Discrete Cosine Transform

DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. The DCTs are commonly connected to Fourier Series coefficients of a regularly and evenly extended sequence whereas DFTs are related to Fourier Series coefficients of a periodically extended sequence. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry whereas in some alternates the input and/or output data are shifted by half a sample. DCT is used in audio and video compression [10]. Nowadays portable EEG devices are available which continuously record and send EEG signals, in-order to preserve information from these EEG signals we need to compress EEG signals. CT is one of the effective signal compression techniques.

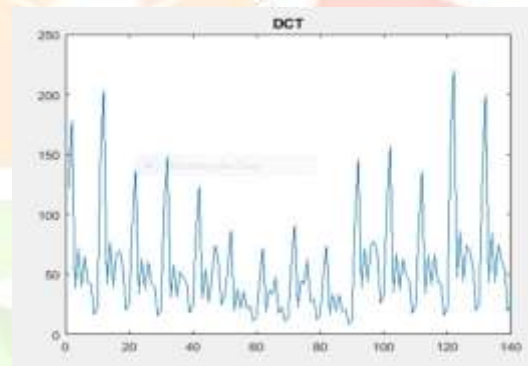


Figure 4. Discrete Cosine Transform

IV. FEATURE EXTRACTION

We usually distinguish features in terms of time domain, frequency domain and time frequency domain [11]. Usually features are extracted from the signals recorded from a single electrode, but in some cases features are calculated from the combination of signals from more than one electrode. We are going to discuss some of the features from the EEG signal in the following session.

4.1 . Non-Stationary Index (NSI)

This feature is a measure of complexity by examining the variations in average over time [12]. The standardized signal is separated into minor portions and the average of each portion is calculated. The NSI is defined as the standard deviation of all means.

4.2 Fractal Dimension (FD)

It is one of the widely used measures of complexity.

4.3 Higher Order Crossings (HOC)

This feature extraction method is comparatively simple and has information compression abilities. It conserves spectral parameters of the signal [13]. It is an efficient feature extraction method.

4.4 Band Power

The most popular features in emotion recognition from EEG signals are power features calculated from different frequency bands. In order to find the power from the bands, we need to apply Fourier transforms to EEG signals. Short Time Fourier Transform (STFT) is applied to find Power Spectral Density (PSD). STFT is more effective to reduce noise.

4.5 Differential Asymmetry

This feature is calculated by the difference in power bands between corresponding pairs of electrodes. This is actually the difference between two features [11].

$$\Delta x = x_l - x_r,$$

where l and r denotes electrodes placed at the left and right hemisphere of the scalp.

4.5 Rational Asymmetry

This is the ratios of features from symmetric electrodes. This is calculated by

$$x_l / x_r$$

V. CLASSIFICATION METHODS

4.1 Support Vector Machine (SVM) Classifier

SVM is the supervised learning model which helps us to classify data. SVM training algorithm assigns new data to one category or the other. An SVM model represents examples as points in space, plotted so that the samples of the distinct groups are divided by a clear gap that is as wide as possible. New samples are then plotted into that same space and predicted to belong to a category based on which side of the gap they fall.

4.2. K Nearest Neighbor (KNN) Classifier.

This method is also used for data classification. An object is classified based on the majority vote of its neighbors. This algorithm is simple compared to other machine learning algorithms.

VI. CONCLUSION

In this paper we present various techniques which are used in automatic emotion detection. We discussed the background details, various signal processing methods, some of the EEG features and classification algorithms. There are lot more features related to emotion recognition, There are lot more features related to emotion recognition, we have covered only some important features. We hope that this paper gives good idea about the automatic emotion recognition to those who are planning to enter into this field of research. Hope this work is helpful to the research community.

REFERENCES

- [1] M. Mohammadpour, S. M. R. Hashemi and N. Houshmand, "Classification of EEG-based emotion for BCI applications," 2017 Artificial Intelligence and Robotics (IRANOPEN), Qazvin, 2017, pp. 127-131.
- [2] S. M. Alarcão and M. J. Fonseca, "Emotions Recognition Using EEG Signals: A Survey," in IEEE Transactions on Affective Computing, vol. PP, no 99, pp 1-1.

- [3] P. D. Purnamasari, A. A. P. Ratna and B. Kusumoputro, "EEG based patient emotion monitoring using relative wavelet energy feature and Back Propagation Neural Network," 2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Milan, 2015, pp 2820-2823
- [4] T. Nepusz, H. Yu, and A. Paccanaro, "Detecting overlapping protein complexes in protein-protein interaction networks of facial actions for natural EEG-based BCI applications", Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), vol 6975, pp 436-446, 2011.
- [5]] P. Ekman, "Facial expressions of emotion: New findings new questions," Psychological Sci. vol. 3, no. 1, pp. 34-38, Jan. 1992.
- [6] A. Hanjalic, L.-Q. Xu, "Affective video content representation and modeling," IEEE Trans. Multimedia, vol. 7, no. 1, pp. 143-154, 2005 FEB
- [7] S. Koelstra, C. Muhl, M. Soleyman, "Deap: A database for emotion analysis using physiological signals," IEEE Transactions on Affective Computing, vol. 3, no. 1, pp. 18-31, 2012..
- [8] G. Kashyap, M. Bora, M. Nishat, Xutong Cui, Sio-Hang Pun and S. Barma, "Analysis of neural electrical activities during elicitation of human emotion based on EEG," 2016 International Conference on Signal Processing and Communication (ICSC), Noida, 2016, pp. .
- [9] M. Teplan, Fundamentals of EEG measurement, Measurement Science Review, pp. 111, 2002
- [10] Salomon, D, "Data Compression. The Complete Reference.", Springer third edition 2004.
- [11] R. Jenke, A. Peer and M. Buss, "Feature Extraction and Selection for Emotion Recognition from EEG ," in IEEE Transactions on Affective Computing, vol. 5, no. 3, pp. 327-339, July-Sept. 1 2014.
- [12] E. Kroupi, A. Yazdani, and T. Ebrahimi, EEG correlates of different emotional states elicited during watching music videos,, in Proc. Int. Conf. Affect. Comput. Intell. Interact., 2011, pp. 457466.
- [13]] P.A. Dickstein, J.K. Spelt, A.N. Sinclair, "Application of a higher order crossing feature to non-destructive evaluation: a sample demonstration of sensitivity to the condition of adhesive joints," Ultrasonics, Volume 29, Issue 5, September 1991,

