Emotion Classification from EEG

Kartic Kaushal[1], Dr. Mahesh Pawar[2], Dr. Sachin Goyal[3], Dr. Ratish Agrawal[4]
P.G. Scholar, DOIT, RGPV, Bhopal, India[1]
Assistant Professor, DOIT, RGPV, Bhopal, India[2,3,4]

***Abstract*—** Emotions are believed to be extremely potent for analyzing the condition of mind. Emotion recognition is a discipline that has been in existence for a long time and so several models have been proposed so far. Many researchers have classified human emotions in terms of two sovereign variables, namely Arousal, and Valence. EEG recordings contain too much noise, thus, we use a combination of discrete features for emotion detection. This study covers recent works on different stages like EEG signal acquisition, features extraction, classification of emotion and conclusions from various studies. A brief description about all of the techniques along with a comparison of all of them has been presented here.

***Keywords*—** EEG; Feature Extraction; Emotion Detection; Valence and Arousal

I. Introduction

Emotions are part of what makes us human. As social animals, interacting with others (human or otherwise) who do not have or understand emotions is an off-putting experience, to say the least. Moreover, as Antonio Damasio has discussed, emotions are very important in our reasoning process: those unable to access their emotions are essentially unable to make even minor decisions. Emotion is a response to two factors, they posit, namely arousal and cognitive labeling. One can detect mental disorders and stress with the basic emotions like happy, sad, surprise, angry etc. Emotions can be estimated by various methods. The first method focuses on the analysis of Speech or Facial expressions to detect the emotions. Second procedure focusses on

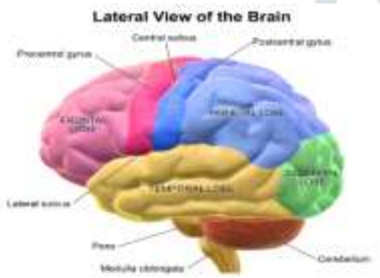


Figure 1. Lateral View of the Brain

peripheral physiological signals, using conductance of skin and Electrocardiography. The last out of three techniques practices Electroencephalography (encephalon = brain), as it determines emotions very accurately. It is recorded by electrodes from the scalp, in the form of electrical signals. These signals are shown using a computer, after amplifying. Executing the frequency transformation, on EEG signals can help in measuring its frequency components and other significant properties. We can recognize the subject's perspective state, on the basis of an EEG signal, to predict if '*the person is feeling sad*' or '*the person is feeling excited*'. Though, it can't apprise the precise essence of the thought.

The EEG signal is mainly categorized into several frequency ranges, namely alpha, beta, gamma, delta, and theta.

Table 1. EEG frequency band [1]

Band	Distribution	Feeling states	Tasks & Behaviours	Physiological Correlates
Delta (0.1–3 Hz)	Broad or diffused, bilateral, widespread	Deep, dreamless sleep, non-REM sleep, trance, unconscious	Lethargic, not moving, not attentive	Not moving, low-level of arousal
Theta (4–7 Hz)	Regional, involve many lobes, lateralized or diffused	Intuitive, creative, recall, fantasy, imagery, creative, dreamlike, switching thoughts, drowsy	Creative, intuitive; distracted, unfocused	Healing, integration of mind/body
Alpha (8–12 Hz)	Regional, involves entire lobe; strong occipital w/eyes closed	Relaxed, not agitated, but not drowsy; tranquil, conscious	Meditation, no Action	Relaxed, healing
Low beta (12–15 Hz)	Localized by side and by lobe	Relaxed yet focused, Integrated	Resting yet alert	Sensorimotor rhythm
Midrange beta (15–18 Hz)	Localized, over various areas. May be focused on one electrode	Thinking, aware of self & Surroundings	Mental activity	Alert, active, but not agitated
High beta (above 18 Hz)	Localized, may be very focused	Alertness, agitation	Mental activity	General activation of mind & Body functions
Gamma (40 Hz)	Very localized	Thinking; integrated Thought	High-level information processing	Information-rich task processing

Valence Arousal Model

This two dimensional model of emotion is by James Russell [2]. Where the dimensions are valence & arousal. Valence for emotion positivity/negativity and Arousal for the excitement level. Respectively every emotion is a prognosis of valence and arousal levels such as excited, calmness, sadness, and happy. However, researchers don't accomplish the complex task of recognizing all emotions because of the similarity like fear and nervousness. Thus, scientists are bounded to conclude main emotions i.e. happy, angry, sad, calm and neutral.

Figure 2. Circumplex Model of Emotions by Russel

OVERALL STRUCTURE

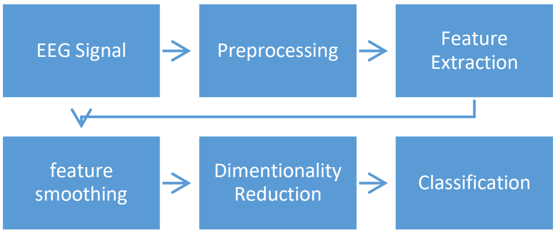


Figure 3. Overall Structure

II. METHODS

EEG PREPROCESSING

Pre-processing is the method of reducing the noises and other external interferences while extracting features from the signal. The signals instigated from the non-cerebral area of the brain are called artifacts. Eradicating the artifacts completely may also remove some of the valuable data of EEG signals. The noises and other external interferences are detached from EEG using Spectral Filtering, Surface Laplacian Filtering, etc [3]. To remove the signals from 4-40Hz, Surface Laplacian Filtering, Bandpass filter is used.

FEATURE EXTRACTION METHODS

To extract specific data from the EEG signals, feature extraction techniques are used. We emphases on different extraction methods i.e. Higher Order Crossing(HOC), Nonlinear Dynamic Analysis, Principal Component Analysis(PCA), Short Time Fourier Transform(STFT) and Mutual Information, Discrete Wavelet Transformation(DWT), Independent Component Analysis(ICA), Statistical Based Feature. The Features could be extracted, based on the frequency and time trait [4].

A. WAVELET TRANSFORM

WT has a vast number of applications in engineering, mathematics and biomedical field. Comparing WT with spectral analysis, WT is more advantageous and WT is also suitable for nonstationary signals. Wavelet is best suited for time-frequency techniques [5]. At lower frequencies, it delivers precise frequency data & precise time data at the higher frequencies [3-4]. Because most signals in the biomedical field always contain high-frequency components with the short time period and low-frequency components with the long time period.

B. PRINCIPAL COMPONENT ANALYSIS

It is a type of dimensional reduction analysis technique used for feature extraction. Dimensional reduction in PCA is attained by projection to lower dimensional space using linear transformation [6]. PCA can effectively reduce surplus information. PCA accepts the data as linear.

C. NONLINEAR DYNAMIC ANALYSIS

In the nonlinear dynamic analysis, the main focus is on the nonlinearity of the data. It capable to be applied on any no. of degrees of freedom. To evaluate the effects of dynamic loading, NDA is a convoluted model, where we assume load as waves rather than values, making analysis much easier [7]. Also, it illustrates epochs' shifting behavior, which further helps in analyzing the EEG and its physiological functions.

D. HIGHER ORDER CROSSING

To reproduce the oscillatory pattern of the EEG wavess is the HigherOrderCrossing's main objective [8-9]. For calculating the crossings, the mean is subtracted from the time series. It is only calculated for alpha and beta signals. The original EEG wave is captured as the first order. Similarly, in succeeding orders, the next wave is achieved by taking the difference of the sequential points of the preceding waves. In order to retain the same number of points at each level, it is required to start ten points from the beginning of the wave. This can be combined with spectral and discriminate analysis to extract the particular feature.

E. STATISTICAL FEATURES

The statistical features obtained from the EEG signal in the time domain are further separated in order to produce separate feature vector for frequency domain & time domain [10].

- Mean *(μ)*
- Standard deviation *(σ)*
- Mean of the *AFD*
- Mean of the normalized *AFD*
- Mean of the *ASD*
- Mean of the normalized *ASD*

where AFD is **Absolute values of the first differences**,
ASD is **Absolute values of second differences**.

F. MUTUAL INFORMATION & SHORT TIME FOURIER TRANSFORMATION

Mutual Information takes care of how each and every electrode's internal pairing and the extraction of statistical dependency features are extracted for emotion recognition.
STFT is a technique to analyze the nonstationary signals and to process signals. It also determines the phase content and the sinusoidal frequency of the local section of a signal as it changes over the time.

G. INDEPENDENT COMPONENT ANALYSIS

ICA transforms the multivariate signal to the independent signals, having component. It confiscates the noises present in the EEG signal to evaluate particular feature which is not associated with one another. Postulate a scalar source wave *x(t)*, and assume vector with Mean = 0 so,

$$\mathbf{P(x(t)) = \Sigma p(x_i(t))}$$

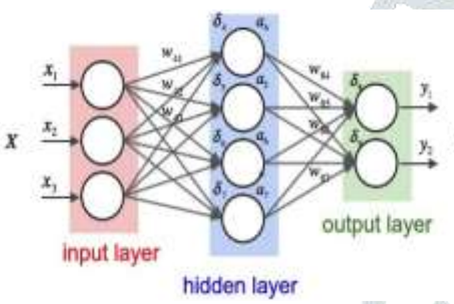
CLASSIFICATION

In order to label the classes and construe a perimeter between them on the basis of their measured features, classification is performed. It can be both supervised as well as unsupervised. Different classification methods are:

A. NEURAL NETWORKS

The information is passed from one node to another, through the interconnected network of neurons (also called, Elements), which is nature's approach to store the information. Useful for both classification and Regression. Within each layer, the neurons are either interconnected or not connected at all. Input, Output, and Hidden are the three different layers of in Neural Network. ANN can be used as, Neurobiological analogy, Real-Time Processing, Ability to fault tolerance. The 3 different kinds of learnings in the NeuralNetwork are Supervised Training, Unsupervised Training, and Reinforcement Training. Under Supervised Learning target class is the one which finds the exact output, which is required. In Unsupervised Training, we have to find the output in the absence of the target class, associated with the problem. Reinforcement learning is the amalgamation of both, Supervised and Unsupervised learning. Classification is the assignment of each object to a specific class.

B. K-NEAREST NEIGHBOR



KNN is an instance based and non-parametric, applied in a supervised learning setting. KNN classifiers learn by comparing the similar test tuples and the training tuples together. In case of an unfamiliar tuple, the configured space for 'k' training tuples is examined by, which are closest to the unfamiliar tuples. These 'k' training tuples are known as the '*K-Nearest Neighbors*' of the unknown tuple.

Figure 4. Neural Network

To determine the Euclidean space among tuples, letsay, $\boldsymbol{K}_1 = (k_{11}, k_{12}... k_{1n})$ and $\boldsymbol{K}_2 = (k_{21}, k_{22}...k_{2n})$, is Dist($K_1$,$K_2$) = $\sqrt{\sum(k_{1i} - k_{2i})^2}$

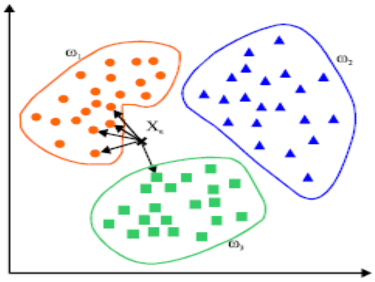
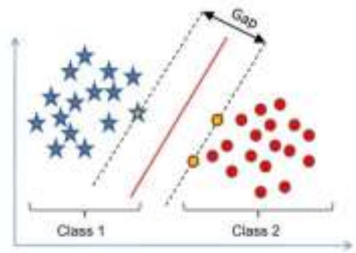


Figure 5. K Nearest Neighbor

C. SUPPORT VECTOR MACHINE

The classification of both nonlinear & linear data is performed using Support Vector Machine. The nonlinear mapping is performed in SVM to transmute the original given data into the higher dimension. It also helps to distinguish the classes from one another. The hyperplane in SupportVectorMachine is found, using margins and support vectors.

Figure 6. Support Vector Machine



D. LINEAR DISCRIMINANT ANALYSIS

LDA approaches are applied in Artificial Intelligence, regularities of data, statistics, and recognition pattern, to discover linear grouping of features which splits two or more classes of objects. Calculating the distance between the samples and the training data of unknown inputs is performed very fast by the LDA. Data is linearly transmuted from higher dimensional space to lower dimensional space by Linear Discriminant Analysis.

Past Studies

Reference Year	Participant	Emotions	Stimulus	Features	Classifier	Result	Real Time
[11] 2008	6	6: Happy Disgust Fear Sad Surprise anger	Audio-visual Movie Clip	Statistical Features: Energy MEE RMS	FCM	-	NO
[12] 2009	26 subjects	4: Angry Joy Pleasure Sadness	Music	PSD and ASM12	SVM	92.57%	NO
[13] 2010	20 subject	Positive Neutral Negative	Pictures from IAPS	LPP	KNN	72.22%	No
[14] 2011	22 students	6 Sad Frustrated Fear Satisfied Pleasant Happy	Audio stimulus with IADS Music stimulus	FD	Threshold	-	Yes
[15] 2012	1 volunteer	5: Happy Angry Sad Relaxed Neutral	Pictures from IAPS	HFD	SVM	70.5%	Yes
[16] 2012	5 subjects	3: Positively	Pictures from	HOC	KNN	90.77%	No

		excited Neutral Negatively excited	IAPS				
[17] 2012	20 subjects	5: Happy Angry Sad Relaxed Neutral	15 Pictures	FD	SVM	70.5%	YES
[18] 2013	10 subjects	2: Happy Unhappy	100 pictures from GAPED and 2 classical music pieces	PSD	Gaussian SVM	75.62%	YES
[19] 2013	11 participants	2: positive Negative	100 pictures from GAPED	PSD	SVM	85.41%	NO
[20] 2015	12 volunteers	5: Neural Happy Sad Tense Sisgust	15 Movie Clips: 3 per emotion	PSD and AI	SVM	93.31%(PSD) 85.39%(AI)	NO
[21] 2015	4 subjects	2: Pleasant and Unpleasant	40 pictures: 20 per Emotion	Features based on ERDS/ERD	SVM KNN	59.9%(SVM) 57.35%(KNN)	NO
[22] 2015	15 subjects	3: Positive Neutral Negative	15 emotional video Clips	Differential entropy(DE)	DBN SVM LR KNN	86.08%(DBN) 83.99%(SVM) 82.70%(LR) 72.60%(KNN)	NO
[23] 2015	Pre-processed Dataset	4: Happy Relax Sad Fear	-	PSD	SVM	88.51%	NO
[24] 2016	DEAP Datasets		Musical video records from DEAP	Statistical features, PSD and FD	SVM	60.7%(Arousal), 62.33%(Valence)	NO

Feature: Power Spectral Density (**PSD**), Spectral Power Asymmetry (**ASM**), Higher Order Crossings (**HOC**), Asymmetry Index (**AI**), event-related synchronization/desynchronization (**ERDS/ ERD**), Fractal Dimension (**FD**) and late positive potential (**LPP**).
Statistical Features: Recoursing Energy Efficiency (**REE**), Root Mean Square (**RMS**),
Classifier: Support Vector Machine (**SVM**), Naive Bayes (**NB**), Quadratic Discriminant Analysis (**QDA**), K-Nearest Neighbors (**KNN**), Linear Discriminant Analysis (**LDA**), Multilayer Perceptron (**MLP**), Filter bank common spatial pattern (**FBCSP**), Deep belief Networks (**DBNs**), and Artificial Neural Network (**ANN**).
Others: Advance Brain Monitoring (**ABM**).

Table 2. Summary of features extraction techniques and classifiers

Advantages and Disadvantages of Feature Extraction & Classification Techniques

These tables explain different feature extraction methods and different classification methods, their advantages and disadvantages, which will help to analyze the emotions.

S.NO	METHOD	ADVANTAGE	DISADVANTAGE
1	WT	1. Analyse the signal with variable window 2. Analysis both time and frequency data	1. Lacking of specific method. 2. Perform limited Heisenberg uncertainty
2	PCA	1. Analysis is reducing the dimensionality without loss of information	1. Data is complicated PCA fails to process those data's.
3	ICA	1. Computationally efficient for large data. 2. Decompose signal into temporal data.	1. Require more computation 2. Not works with determinate cases
4	STFT	1. Easy to understand 2. Fixed slide window length.	1. Cannot de-noising 2. Trade-off between time and frequency.
5	HOC	1. Performance should be high 2. Provide Optimized result	1.Difficult to choose the random data

Table 3. Comparison of WT, PCA, ICA, STFT, HOC Extraction Methods

Table 4. Comparison of LDA, SVM, KNN, NN Classification Methods

PROPOSED METHODOLOGY

Based on recent researches for Emotion Recognition techniques, and considering characteristics of EEG waves presented previously, we propose in this section, a

S.NO	METHOD	ADVANTAGE	DISADVANTAGE
1	LDA	1. Extremely Fast 2. Low Requirement 3. Good Result	1. Fail to discriminate functions like variety of features 2. Complex structure
2	SVM	1. Good Generalization 2. More Performance	1. Computational complexity high
3	KNN	1. Easy to understand 2. Easy to implement	1. Poor runtime performs 2. Sensitive to irrelevant and redundant features.
4	NN	1. Easy to train. 2. Accurate Pattern classification.	1. Needs training to operate. 2. Requires high processing time for large network

combination of techniques. By implementing this architecture we aim to achieve better rates in Emotion Recognition. We will implement one of the Gene selection from microarray data in Bioinformatics to test its efficiency when combined with SVM as a classifier.

CONCLUSION

Detection of emotions using EEG signals is still a developing research area. Researchers will extemporize the efficiency and accuracy in deciding the appropriate method which can be used in signal Classification. The accuracy of emotions can be dissimilar from one extraction technique to another. The mishmash of multiple feature extraction and the classification techniques delivers enhanced outcomes.

Augmented Reality (AR) can deliver superior performance in emotion recognition than any other approaches in this field.

References

[1] Collura, T.F.: The Measurement, Interpretation, and Use of EEG Frequency Bands (1997)

[2] Russell, J.A.: A circumplex model of affect. J. PSP 39(6), 1161–1178 (1980)

[3] Murugappan, N. Ramachandaran, and Y. Sazali, Mohd "Classification of Human Emotion from EEG discrete wavelet" J. Biomed. SCI. Eng., vol. 3, pp-390-396, Apr-2010

[4] Mr. C. E. Mohan Kumar. Mr. S. V. Dharani Kumar "Wavelet Based Feature Extraction Scheme of Electroencephalogram" in IJIRSET.

[5] Ales Prochazka and Jaromır Kukal, Oldrich Vysata "Wavelet Transform Using for Feature Extraction and EEG Signal Segments Classification" in IEEE.

[6] Reza khosrowbadi, Kai Keng Ang, and Abdul Wahab "ERNN: A biologically Feedforward Neural Network to Discriminate Emotion from EEG Signal" IEEE neural network and learning systems. Vol. 25, No 3, Mar-2014

[7] Garrett, D., Peterson, D. A., Anderson, C. W., & Thaut, M. H."Comparison of linear, nonlinear, and feature selection methods for EEG signal classification". Neural Systems and Rehabilitation Engineering, IEEE Transactions on, 11(2), 141-144, 2003.

[8] Petrantonakis, P.C., Hadjileontiadis, L.J.: EEG-based emotion recognition using hybrid filtering and higher order crossings. In: 3rd International Conference on Affective Computing and Intelligent Interaction and Workshops (2009)

[9] Petrantonakis, P., Hadjileontiadis, L.: A novel emotion elicitation index using frontal brain asymmetry for enhanced EEG-based emotion recognition. IEEE Trans. Inf. Technol. Biomed. 15(5), 737–746 (2011)

[10] JenkeR,PeerA,BussM.Featureextractionandselectionforemotionrecognitionfrom EEG.IEEETransAffectComput.2014;5(3):327-339.

[11] Murugappan, M., Sazali, Y., Hazry, D.: Lifting schema for humanemotion recognition using EEG. In: International Symposium on Information Technology (2008)

[12] Lin, Y.P., Wang, C., Wu, T.L., Jeng, S.K., Chen, J.H.: EEG-based emotion recognition in music listening: a comparison of schemes for multiclass support vector machine. In: IEEE ICASSP (2009)

[13] Schuster, T., Gruss, S., Kessler, H., Scheck, A., Hoffmann, H., Traue, H.: EEG: pattern classification during emotional picture processing. In: 3rd International Conference on PErvasive Technologies Related to Assistive Environments, vol. 67 (2010)

[14] Liu, Y., Sourina, O., Nguyen, M.K.: Real-time EEG-based Emotion Recognition and its Applications (2011)

[15] Anh, V.H., Van, M.N., Ha, B.B., Quyet, T.H.: A real-time model based support vector machine for emotion recognition through EEG. In: ICCAIS (2012)

[16] Haiyan, X., Konstantinos, N.: Affect recognition using EEG signal. In: MMSP Conference (2012)

[17] Anh, V.H., Van, M.N., Ha, B.B., Quyet, T.H.: A real-time model based support vector machine for emotion recognition through EEG. In: ICCAIS 2012 (2012)

[18] Jatupaiboon, N., Pan-ngum, S., Israsena, P.: Real-Time EEG-based happiness detection system. Sci. World J.(2013)

[19] Jatupaiboon, N., Pan-ngum, S., Israsena, P.: Emotion classification using minimal EEG channels and frequency bands. In: The 10th International Joint Conference on Computer Science and Software Engineering, May 2013

[20] Lui, S., Meng, J., Zhang, D., Yang, J., Zhao, X., He, F., Qi, H., Ming, D.: Emotion recognition based on EEG changes in movie viewing. In: 7th Annual International IEEE EMBS Conference on Neural Engineering (2015)

[21] Hou, C.L., Mountstephens, J., Teo, J.: EEG-based recognition of positive and negative emotions using for pleasant vs. unpleasant images. Int. J. Recent Adv. Multi. Res. 02(06), 181–485 (2015)

[22] Zheng, W.-L., Lu, B.-L.: Investigation critical frequency bands and channels for EEG-based emotion recognition with deep neural networks. IEEE Trans. Auton. Ment. Dev. 7(3), 162–175 (2015)

[23] Lokannavar, S., Lahane, P., Gangurde, A., Chidre, P.: Emotion recognition using EEG signals. Int. J. Adv. Res. Comput. Commun. Eng. 5(5), 54–56 (2015)

[24] Atkinson, J., Campos, D.: Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers. Int. J. Expert Syst. Appl. 47(C), 35–41 (2016)