IJITKM Volume 7 • Number 1 • December 2013 pp. 1-5

Emotion Recognition Using Electroencephalography (EEG): A Review

Mandeep Singh[1], Mooninder Singh[2], Surabhi Gangwar[3]

Department of Electrical & Instrumentation Engineering, Thapar University, Patiala, INDIA
[1] Mandy_tiet@yahoo.com, [2]mooninder@gmail.com, [3] surabhi.g786@gmail.com

Abstract

Emotions are believed to be extremely potential for analysing condition of mind. Recognition of emotions by physiological means is a subject of interest for both psychologists as well as engineers. Many researchers have classified human emotions in terms of two independent variables, namely arousal and valence. This paper includes a stepwise study of stages involved in ElectroEncephaloGraphy (EEG) signal analysis for human emotion detection. The review covers some recent works on these stages like EEGsignal acquisition, features extraction, classification of emotion and conclusions from various studies.

Keywords: Emotion detection, Electroencephalography,Arousal and Valence.

1. Introduction

One of the commonly accepted definitions of emotion is “A natural instinctive state of mind deriving from ones circumstances mood or relationship with others. Emotion have important role in interaction and communication between people.Emotion can be expressed either verbally through emotional vocabulary, or by expressing non-verbal cues such as intonation ofvoice, facial expressions and gestures. In this topic, decoding of emotional cues is essential tocorrectly explain a message.The Greek philosopher ***Aristotle***thought of emotion as a stimulus that evaluates experiences based on thepotential for gain or pleasure. If someone smiling and shouting “Shut up” at someone it does not have the same meaning as saying it while aggressively shouting“SHUT UP”.Emotionidentification has recently been considered as a key element in advanced human-computer interaction. In seventeenth century, Descartes consideredemotion to mediate between stimulusand response.Most of the researchers have focused on facialexpression recognition and speech signal analysis forassessing emotions [1, 2].Mostly techniques to understand the emotions are mostly based on a single modality such as Positron Emission Tomography (PET),Functional Magnetic Resonance Imaging (fMRI), ElectroEncephaloGraphy (EEG) or static face image or videos.Psychologists say that human emotions can becategorized into a small number of cases.Ekman et al. [3] found that six different facial expressions (angry, sad, disgust, happy, fearful and surprise) were categorically recognized by humans from distinct cultures using a standardized stimulus set. Inother words, these facial expressions were stable over age brackets, and were consistenteven in people blind by birth.

There are many difficulties in automatichuman emotion identification. Since emotion express natural instinctive state of mind,the outward expression may be voluntarily controlled as per the environment or the circumstances. A person when feeling angry may shout at his child, but may suppress this in front of his boss.Straightforward connection of facialactions with neural signals or with emotions may not be correct.EEG signal changes according to the emotion state. On the other hand changes that occur in EEG signal cannot be voluntarily controlled and hence become a better indicator of emotions.One of the motives to study detection of emotions is to make robots communicate with humans in natural way. Emotion detection using EEG signals can be of help in this communication it may be mentioned here thatto design experiments to single out a unique emotion is a very challenging task .As even small changes in the experimental setup may lead to significance differences in the results. A large part of communication is done nowdays by computer or other electronic devices.But this interaction is a lot different from the way human beings interactnaturally. MostlyCommunicationbetween human beings involves non-verbal signs, and the social form ofthis communication is important. On the other hand the interaction between humans and computers is done there, use of a simple keyboard and mouse, that worksfine for many cases. And now many other forms of human computer interaction have been invented.Speech recognition by computers is improving and this is becomingmore and more common in consumer products. It is speculated that the speech recognition process shall be able to detect the emotion by sensing the tone of the speech. Arm movement is used when playing games on game console.

2. Quantification of Emotion

Several researchers have expressed human emotion on two dimensional planes. The orthogonal components considered in this classification are:-

(i) Valence
(ii) Arousal

It is a pictorial representation of some of the emotions is shown in figure 1

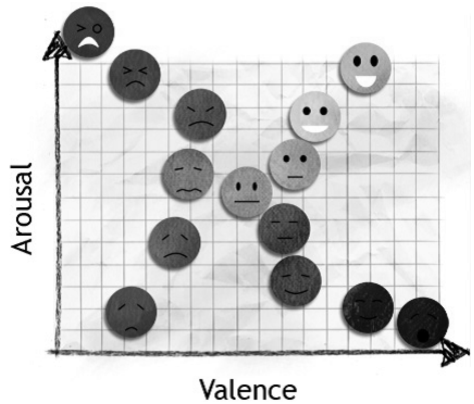

Figure 1: Different emotions on the valence and arousal scale

2.1 Valence

Most apparent things about emotion in EEG measurements is the differencebetween the left and the right hemisphere. It has been suggested that information aboutthe valence dimension can be found in this difference, which is called the hemisphericalemotional valence (Hev).

2.2 Arousal

Where there is a lot of information about EEG properties of the valence dimension, lessis known about how to measure arousal using EEG signals. Many studies have been done but the results are less obvious than for the valence dimension. The main conclusion from earlier researchshows that the right posterior hemisphere has something to do with arousal. This hasalso been confirmed the research of Aftanas et al. state that rightposterior hemispheres and left anterior both hemispheres are involved with arousal[4].

3. Signal Acquisition

Functional Magnetic Resonance Imaging (FMRI) andPositron Emission Tomography (PET) have a good spatial resolution, but are very slow, because they depend onchanges in composition of blood. EEG on the other hand gives immediate responses,but is not able to reactthe exact location of the brain activity. Because of hightime-resolution, ease of procedure andlow cost, many researchesuse EEG signal. Since brain activity only produces very weak signals, EEG signals contain a lot ofbackground noise. EEG signal can be used for epilepsy detection [5]before using the signals for emotion recognition; they have to bepreprocessed, in order to remove unwanted noise.

4. Preprocessing

Preprocessing is a state of processing EEG signal in such a way to reduce noises, artifacts and other external interferences. The signals originated from non-cerebral region of brain are called artifacts. The complete removal of artifacts may alsoremove some of the useful information of EEG signals. There are number of methods uses by researchers to avoid artifacts in EEG recordingwhile retaining the useful information. The goal of this preprocessing step is to reconstruct the original brain activity. In addition to noise/artifacts removal. Numbers of other steps are executed to obtain meaningful information.These steps are explained in the subsequent section.

4.1 Referencing

EEG signals are a recording of the voltage at different electrodes. Basically this measurement should only represent the electrical activity on that spot. Voltage is a relative measure. The measurement is compared to the voltage at a reference site, but thisresults in measurements that reflect the both local activity and activity at the reference site.Because of this, the reference should be chosen such that the activity at the reference site is almost zero. Unfortunately some of noise is also picked up by the measuring electrodes. The final EEG signal is thus sum of brain activity, reference signal and noise as shown on Figure 2.

The sole idea of prepossessing is to extract the original brain activity signal[6].

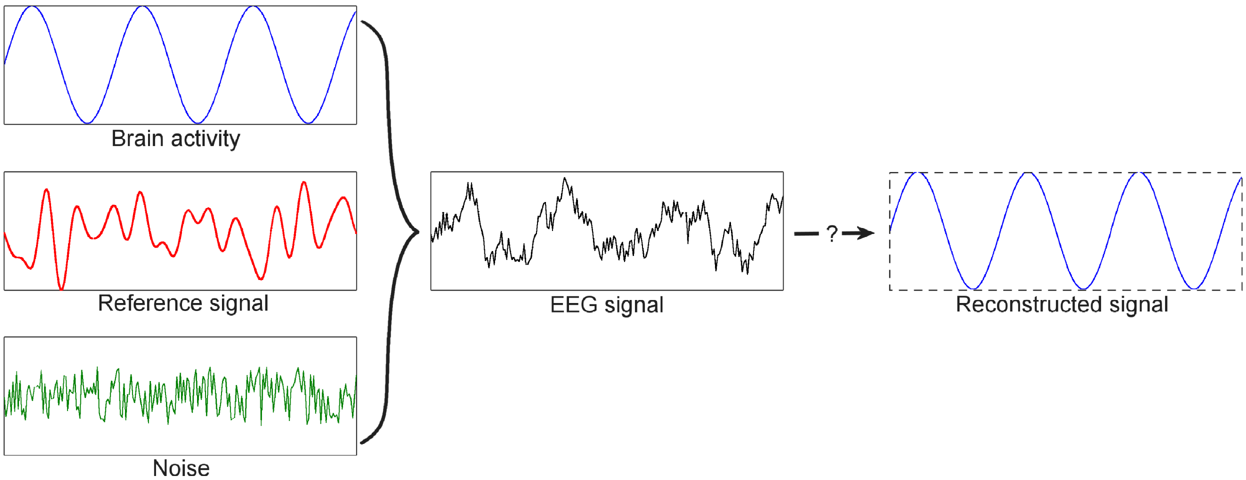

Figure2: EEG signals as a combination of brain activity, reference activity and noise

4.1.1 Common reference

A widely used method of referencing is the common reference technique. In thismethodone common reference isusedfor all electrodes, preferably a reference at a large distancefrom all electrodes. The activity at the reference site effects all measurements equally. Differences between electrode measurements still contain all information needed.

4.1.2 Average reference

Another method is the average reference. The average reference subtracts the averageof the activity at all electrodes from the measurements. This method is based on theprinciple that the activity in the whole head at every moment sums up to zero. Therefore,the average of all activity represents an estimate of the activity at the reference

4.2 Noise and artifacts

The brain produces electrical activity in the order of microvolts. As these signalsare very weak, it usually contains a lot of noise. The recorded EEG signals are usually contains noises (due to power line interferences and due to external interferences), Sources of noise are static electricity or electromagnetic fields produced by surrounding devices. In addition to this externalnoise, the EEG signal is most of the times heavily influenced by artifacts that originatefrom body movement like Ocular (Electrooculogram), Muscular (Electromyogram), Vascular (Electrocardiogram) and Gloss kinetic artifacts. For example, eye blinks or other eyemovements produce large spikes in the EEG signal. Other muscle movements also leavetheir mark in the brain signal. In many studies the participants are asked not to moveor to blink as few times as possible. However, in many practical situations this is notfeasible. Consequently, preprocessing of the signal is done to remove these noises and artifacts.

4.2.1 Removal of Noise

Noise that is present in the EEG signals can be removed using simple filters. Therelevant information in EEGfor emotion recognition is found in the frequenciesbelow 30Hz. Therefore, all noise with higher frequencies Like noise from the electrical network has a fixed frequency of 50Hz ,can be removed using a low pass filter..Band pass filters can also divide the EEGsignals into frequency bandswhich can be analyzed separately.

4.2.2 Removal of Artifacts

Artifacts are more difficult to remove, because they are not present all thetime, and not always in all electrodes.Second disadvantage of artifacts over othernoise is the relative high voltage as compared to the normal

EEG signals. Many solutions for the problem have beensuggested.One simple method of removing artifacts is simply using a high pass filterto remove the frequencies below 1 or 2Hz. This method assumes that there is not much brainactivity with very low frequencies, and that artifacts occur at a lower frequency. One advantage of this method is that its implementation is very simple and it can be combinedwith the low pass filtering to remove noise with higher frequencies. But thismethod is not very precise, and might remove some useful information as well[6].

5. Feature Extraction

Meaning of Feature extraction is extracting useful information from the signal. Features are characteristics of a signal that are able to differentiate emotions. The difficulty is in identifying the features to be extracted from the signal. Feature selection is a simple process. Those features are selected that have the highest mutual information with the required output. Further there should be low mutual information between different features. An overview of the featuresthat were used for emotion recognition is given in table 1.

Table 1: Use of different features in earlier research for emotion recognition

	MUSHA et.al 1997[7]	VOURKAS et.al 2000[8]	CHOPPIN et.al 2000[9]	CHANEL Et.al 2000[10]	SAVRAN Et.al 2006 [11]	ROBERT HORLING 2008[6]
EEG frequency band power			X	X	X	
Cross-Correlati-on EEG band power	X		X		X	X
Peak frequency in alpha band			X			X
Hjorth parameter		X	X			X

6. Classification

After extracting the desired features, recognition of emotion is done by a suitable classifier. A classifier is a system that divides some data into different classes, and gives the relationship between the features and the emotion that belongs to that part of the EEG signal. There are several methods of classification like naive bayes classifier, artificial neural network, support vector machine,Mahalanobis (MD) distance based Classifier and many more classifiers are used for this purpose.

Robert Horling divided training data into three parts; one is used for testing while the other two are used for training the classifier. The classification rate for valence dimension has been found to be 31% for both Enterface06 and self-collected experimental data.Using a neural network, the classification rates were 31% and 28% respectively for valence and arousal. A naive Bayes classifier produced slightly lower results of 29% for valence and slightly better results for arousal i.e. 35% [6]

Frantzidis.C et.al (2008) classified an arousal dimension of human emotions from fusion of skin conductance and EEG signals(ERPs at Pz and Cz electrode and delta frequency oscillations) using a neural network classifier. The classification results obtained for emotion state Joy - 80%, Fear- 100%, Happiness- 80%, and Melancholy – 70% [12].

Frantzidis.Cet.al(2010) discuss the classification of neurophysiological data obtained through EEG on 56(28 males and 28 females) volunteers by using pictures selected from the International Affective Picture System, into four emotional states. The classification of the emotional states high valence high arousal "HVHA", Low valence high arousal "LVHA", high valence low arousal "HVLA", low valence low arousal "LVLA" were achieved by using the Mahalanobis distance(MD) based classifier and support vector machines (SVMs). EEG was recorded with Ag/AgCl electrodes placed at 19 positions on the scalp as per the 10–20 International System. The sampling rate was chosen as 500 Hz [13]. The classification accuracy obtained is shown in the table 2.

Table 2: The classification results obtained using different classifiers

Classifier	HVHA	HVLA	LVHA	LVLA	Total
MD	85.71%	82.14%	78.57%	71.43%	79.46%
SVM	85.71%	85.71%	71.43%	82.14%	81.25%

Hosseini, Seyyed Abed et.al (2010) described the emotion classification into two states. The features were extracted using Higher Order Spectra methodology,Using Genetic Algorithm for feature selection. SVM as a classifier gave average accuracy of 82% for the two emotional stress states[14].

7. Conclusion and Future Scope

Most of the previous attempts of emotion recognition with the use of EEG signals are mainly focused on collecting data from the autonomic nervous system.The literature survey brings out two highly divided opinions. One group of researchers obtained low accuracy of emotion classification using EEG signal only. This group is of the opinion that after physiological signals like galvanic skin resistance, heart rate, respiration rate etc. be used for obtaining high accuracy. Another group is of the view that EEG signal alone is sufficient for emotion classification, though with a little lower accuracy.It is proposed that only EEG signals foremotion recognition be used wherein different features from EEG signalsareextracted.These signalsbe used to classify the emotions using neural network two state classifier the selection of features and classifiers be made so as to improve the accuracy of classification.

References

[1]H.Bung.andS.Furui, “AutomaticRecognition and understanding of spoken languages- a first step toward natural human machine communication”,*Proceedings of IEEE*, vol. 88, issue:8,pp.1142- 1165.Doi 10.1109/5.880077Aug. 2000.

[2]R.Cowie, E.Douglas, N.Tsapatsoulis, G.Votsis,G.Kollias,W.Fellenz and Taylor J.G, “Emotion Recognition in humancomputer interaction”, *Transactions IEEE Signal Processing*, Volume:18 Issue:1 pp.32-80 doi 10.1109/79.911197Jan 2001

[3]Ekman, R.W Levenson andW.V. Friesen “Autonomic nervous system activity distinguishing among emotions.”*Science 221* vol. 221, no.4616, pp.1208– 1210.Doi10.1126/science.6612338 Sep 1983

[4]L.I.Aftanas,N.V.Reva,A.AVarlamov,S.V.PavlovS.V. and V.P.Makhnev“Analysis of evoked EEG synchronization and desynchronization in conditions of emotional activation in humans: Temporal and topographic characteristics. *Neuroscience andBehavioral Physiology”.Springer,Neuroscience and Behavioral Physiology*, Vol. 34, No. 8, 2004 pp. 859-867.

[5] Mandeep Singh, Sunpreet Kaur ,“Epilepsy Detection using EEG: An Overview”, *International Journal of Information Technology & Knowledge Management*, Val 6, no1, 2012 pp.3-5.

[6] Robert Horlings, “Emotion recognition using brain activity”, *Delft university of technology, Man-Machine Interaction Group*, 27 March 2008.

[7] T.Musha,Y.Terasaki,H.A. Haque, and G.A. Ivanitsky “Feature extraction from EEGs associated with emotions” *springer ,Research and Development in Intelligent Systems XXIV: Proceedings of AI-2007 The twenty seventh SGAI international conferenceinnovative techniques and application of artificial intelligent.(2007)*

[8] M.Vourkas, G.Papadourakis, and S.Micheloyannis. “Use of ann and hjorth parameters in mental-task discrimination”*Advances in Medical Signal and Information Processing.First International Conference on (IEE Conf. Publ. No. 476)*PP.327-332.doi10.1049/cp:20000356 Sep 2000

[9] A.Choppin. “EEG-based human interface for disabled individuals: Emotion expression with neural networks”. *Master's thesis, Tokyo Institute of Technology*.2000

[10] G.Chanel, J. Kon, D. Grandjean, and T.Pun”Emotion assessment: Arousalevaluation using EEG's and peripheral physiological signals”.*Technical Report ,Computer Vision Group,Computing Science Center, University of Geneva*, Dec. 2005.

[11] A.Savran, K.Ciftci,G.Chanel, J.C.Mota,L.H.Viet,B.Sankur,L.Akarun, A.Caplier, and M.Rombaut“Emotion detection in the loop from brain signals and facial images”.*IEE Computer society* vol.2 issue1 pp. 18-31, Doi http://doi.ieeecomputersociety.org/10.1109/T-AFFC.2011.15,jan-march 2012

[12] Frantzidis, C. A., Lithari, C. D., Vivas, A. B., Papadelis, C. L., Pappas, C., & Bamidis“Towardsemotion aware computing: a study of arousal modulation with multichannel event-related potentials, delta oscillatory activity and skin conductivity responses”*In Proceedings of BIBE, .pp.1-6 (2008)*

[13] Frantzidis, C. A., Bratsas, C., Papadelis, C. L., Konstantinidis, E., Pappas, C., & Bamidis, P. D. “Toward emotion aware computing: An integrated approach using multichannel neurophysiological recordings and affective visual stimuli”. *IEEE Transactions on Information Technology In Biomedicine*vol.14 no.3 pp.589-597 (2010).

[14] Hosseini, S. A., & Khalilzadeh, M. “AHigher order spectra analysis of EEG signals in emotional stress state*s”.IEEE computer society,Second international conference on information technology and computer science*.doi(http://doi.ieeecomputersociety.org/10.1109/ITCS.2010.21) ,2010.