IJITKM 0973-4414 Volume-8, Number-2 Jan-Jun 2015 pp. 142-149 **Impact Factor 2.8** available online at www.csjournalss.com

Selection of attribute combinations of ERP's for classification of emotions along arousal axis

Mandeep Singh[1]Mooninder Singh[2]Money Goyal[3]
[1, 2, 3]Department of Electrical & Instrumentation Engineering,
Thapar University, Patiala, India
[1]mandy_tiet@yahoo.com [2] mooninder@gmail.com[3] goyal1990@gmail.com

Abstract: Emotions play a key role in our daily interaction with the outside world. The emotions govern our quality of relations within the society. The emotion detection becomes necessary for developing an affective Human-Computer interface. In this paper we have developed a two class emotion classifier based on Electroencephalogram (EEG) signals. The EEG signalshave beenacquired from five subjects on three frontal electrodes namely Fz, F3 and F4. The images provided by International Affective Picture System (IAPS) have been used for evoking emotions. The ERP potentials P100, N100 and the two latencies corresponding to these bio potentials have been extracted for every class of emotion from preprocessed EEG signals. The training and testing has been performed on 11 combinations of the extracted features. The LIBSVM classifier (RBF kernel) with 3 fold cross validation has been used for classification of emotions along arousal axis into two classes. When emotions are classified subject wise, it has been found that the accuracy remains consistently high (above 75%) on the attribute combinations(P100, Nt100), (P100, Pt100) and (P100, Pt100, N100, Nt100). From the 11 combinations processed to classify emotions along arousal domain, it has been found that the attribute combination of(P100,Pt100,N100,Nt100)gives the best results on all three electrodes used followed by (P100,Nt100) and (N100,Nt100). An average accuracy of 66.26% has been achieved for (P100, Pt100, N100, Nt100), 65.59% for (P100, Nt100), 63.89% for attribute combination (N100, Nt100).

Keywords: EEG, Emotions, Event related potential (ERP), Feature Extraction

1. Introduction

Emotion can be defined as the particular activity of brain and a reflection of human expressionsunder distinct environmental conditions [1]. It is a versatile phenomenon which can control the reactions and behavior of the person depending upon his mental state whether he is happy, angry, frustrated, sad, excited and scared.Different model on emotionswere given by researches like Darwin, Plutchik and Ekman. Plutchik considered that there are eight basic emotions such assurprise, sadness, disgust, acceptance, joy, anger, fear, joy, and curiosity [2].whereas Ekman considered that all emotions are made up of six basic feelings namely happiness, sadness, anger, fear, disgust and surprise [3].The emotions are being studied not only to develop the Human - Computer Interface (HCI) for a population with locked in conditions but as well to study what's going in a mind of persons involved in mission critical operations. For example, a pilot of aircraft driving in a bad mood is not only harmful to himself but also to other passengers on the same aircraft.Thus it is not only essential to study emotions but it becomes essential to propose a methodology to take away the participants from high arousal situation to low arousal situation of mind.Many methods were proposed for emotion recognition using facial expression, gesture and voice of human beings but these responses can be spurious by participants under observation. So it becomes essential to perform recording of brain signals obtained by placing electrodes on scalp of subjects. Other advantages of using EEG signals for emotion classification are that it involves simple and portable hardware, direct measurement of electrical activity, and high temporal resolution [4].The quantification of emotions became possible after representing them in a three dimensional plane. Russell, J.A. (1980) proposed a circumflex model of affect in which emotions were illustrated in a two dimensional space. According to his approach pleased was represented the x-axis and unpleased was represented along y-axis. The emotion describing words were so arranged that the like meaning words were closer while the opposites wasarranged diagonally [5]. Later this model was improved by Lang et al where the two dimensions were characterized by valence and arousal [6]. Two classes of emotions is divided along x axis and y axis namely valence and arousal as shown in Figure 1.

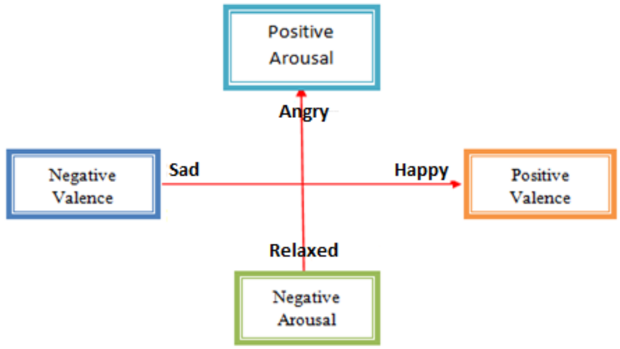

Figure 1: Dimension of emotions

2. Review

Picard, R.W*et al.* (2001) in their research study worked on eight classes of emotions namely grief, love, hate, romantic love, nature, joy including neutral. The emotions were invoked as per the guidelines laid down by Clynes [7]. To recognize eight emotional states, the data was gathered from single subject using four sensors namely an Electromyogram, Photoplethysmyograph, skin conductance sensor and Hall Effect respiration sensor. The statistical features such as mean and standard deviation of signals were selected for classification of emotions. The classification of emotional state was performed with Maximum a Posteriori (MAP) classification technique using Fisher analysis. An accuracy of about 80% to 90% was achieved. Chanel, G *et al.* (2007) classified human emotions along the arousal axis using the combination of EEG signals and other physiological signals such as Galvanic Skin Resistance (GSR), Blood Pressure (BP), and Heart Rate (HR) were extracted. The statistical features such as mean value of the physiological signal and short-time Fourier Transform on the basis of time frequency domain from EEG signal was extracted. The classification of emotions into three emotional states namely negatively excited, positively excited and calm-neutral states was performed. The classification was performed using Linear Discriminant Analysis and a Support Vector Machine using either EEG or peripheral features. It was found that using EEG to assess valence and arousal in emotion is better than peripheral signals [8]. Horlings, R. (2008) classified emotions into five classes along arousal and valence axis by using the self collected EEG signals from ten subjects and the EEG data acquired in eNTERFACE 2006 workshop [9] .The emotions were invoked using images from IAPS dataset. The features used were EEG frequency band power, cross-correlation between EEG band powers, peak frequency in alpha band and Hjorth parameters. The classification was done using 3 fold cross validation using a neural network and a naive Bayes classifier. With neural networks, classification rate was slightly lower than support vector machines and classification rate was achieved up to 32% for valance dimension and 37% for arousal dimension [10].

Murugappan, M *et al*. (2009) collected EEG data from 20 healthy participants when stimulated by audio-visual stimuli. The emotion was classified into five classes namely disgust, happy, surprise, fear and neutral. The EEG signal was decomposed into five different frequency bands (delta, theta, alpha, beta and gamma) using wavelet transforms. The classification was performed using 5 fold cross validation with K Nearest neighbor (KNN) & Linear discriminate analysis (LDA) classifier. An average accuracy of 79.14% was achieved and a maximum subset emotion rate of 91% on disgust, 88% on happy, 60% surprise, 73.75% fear and 87.5 % on neutral emotions was obtained [11].

Frantzidis, C *et al*. (2010) acquired the EEG data from 28 healthy subjects by using images from IAPS datasetfor evoking emotions [12]. The emotions were classified into four emotional states in which valence discrimination was performed first and after that arousal discrimination was performed. The attribute extracted was event related potential for three central electrodes namely Fz, Cz and Pz. The Classification was done by usingMahalanobis distance (MD) and Support Vector Machine (SVM) in various chosen kernels namely linear, polynomial and RBF kernel [13]. The classification accuracy achieved is shown in table1.

Table 1: The classification accuracy achieved using different classifiers

Classifier	HVHA (%)	HVLA (%)	LVHA (%)	LVLA (%)	Total (%)
Mahalanobis distance	85.71	82.14	78.57	71.43	79.46
Support Vector Machine	85.71	85.71	71.43	82.14	81.25

Khosrowabadi, R *et al*. (2010) collected EEG data from twenty six subjects when images from IAPS dataset were used for evoking emotions from eight channels. The attributes was extracted using the magnitude squared coherence of the EEG signals for classification of emotions into four states namely calm, happy, sad and fear. The boundaries of the EEG features were then extracted using self-organizing map. The classification was performed using 5-fold cross validation with k-NN as a classifier with accuracy achieved up to 84.5% [14]. Xu, H *et al* (2012)used the eNTERFACE06 database for classifying into three emotional states namely positively excited, neutral and negatively excited from 54 electrodes. The features in both time and frequency domains such as statistical, narrow-band, higher order crossing and wavelet entropywere extracted. Through the use of k Nearest Neighbor classifier (kNN), the obtained mean correct classification rates of 90.77% on the three emotion classes [15].The eNTERFACE 06 EEG database has been used by number of other researchers for recognition of emotions and different attributes such as Power Spectral Density (PSD), Short Time Fourier Transform (STFT) Event Related Potential (ERP), Entropy, Power and Variance on the basis of time frequency domain were extracted and the classifiers such as ANN and Naïve Bayes were used for classification of emotions into two classes [16] [17] [18] [19] [20].
Singh, M *et al*. (2013) extract the EEG signal from three participants which was acquired by emotion evoking pictures from IAPS. The EEG data was collected from three electrodes namely Cz, F3 and F4 for classifying emotions into two classes along valence axis. The Attribute extracted for emotion classification was event related potential and average of event related potential. The classification was done using support vector machines as classifier [21] [22].

3. Data collection & preprocessing of EEG signal

The methodology used for acquisition and classification of emotions is described in Figure 2.

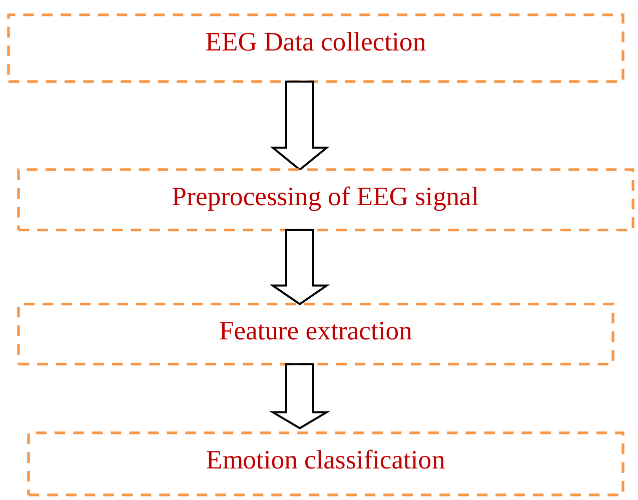

Figure 2: Flowchart for emotion classification

The EEG data has beencollected from five healthy male subjects with no history of any medical disorder.For acquiring the EEG signals, the BIOPAC data acquisition unit MP150 interfaced with EEG cap has been used [23].The data has been acquired by placing a cap on the head of a subject as per 10-20 International system [24]. To make contact between electrodes and the scalp, EEG gel has been used. Out of 20 electrodes available on EEG cap, three frontal electrodes namelyF3, F4 and Fzhave been used for classification. Emotions have been evokedby stimulating the subject with images provided by International affective picture System (IAPS). These images from IAPS werecollected at university of Florida by the scientists of National Institute of Mental Health Center for

Emotion. The images belonging to High Valence High Arousal and High Valence Low Arousal have been shown to the subjects.The images shown to subjects areof different categories such as nature, love, baby, snake, grave etc. Every image is shown to subject for 1second followed by plus symbol for 1.5seconds.Using perfect synchronization between the presentation system and the data acquisition system, EEG data has been acquired from the subjects at sampling rate of 500 samples per second.
After the acquisition of signal, the EEG data has been preprocessedin offline mode by ACQ4.2 software provided by BIOPAC[25].The acquired EEG signals have been brought in the range of 0.5 to 40 Hz by using a low pass IIR filter followed by high pass IIR filter. The low pass filter with cut off frequency of 40 Hz followed by high pass filter with cut off frequency of 0.5 Hz has been applied on the raw EEG signal. The comb band stop filter with a notch frequency of 50Hzhas beenused to remove any power noise interference.
Figure 3 the preprocessed EEG signals for one of the subjects.

Figure 3: Filtered EEG signals on 10 electrodes.

4. Feature extraction
The filtered data has been used for feature extraction. The ERP potentials namely P100, PT100, N100 and NT100are extracted for each class of emotions from the acquired EEG signal.

P100 is the maximum going peak observed between 80ms to 120ms after the onset of stimuli, so P100is known as maximum ERP of participant in the time limit of 80 to 120ms.PT100 is the latency which corresponds to the time(in ms) whenP100occurs.N100 is minimum potential observed between 80ms to 120ms after the onset of stimuli, So N100is known as the minimum ERP of the participant in the time limit of 80 to 120ms. SimilarlyNT100 is the latency which corresponds to the time (in ms) whenN100 occurs.

5. Classification& Results
The extracted attributes has been used for classification of emotions. The classification of emotions has been done along arousal axis into two classes namely High Valence High Arousal and High Valence Low Arousal. The LIBSVM classifier (RBF kernel) with 3 folds cross validation has been used to avoid over fitting problem [26]. The classification is performed subject wise. The training and testing of each subject has been performed separately on 11 combinations of the four extracted attributes. It is performed in such a way that total of 70% samples has been used to train the model. After getting the desired value of cost factor and gamma, the best model has been tested over remaining 30% of the test samples of that subject.The classification has been performed on eleven combinations of the four attributes namely (P100,Pt100), (P100,N100), (P100,Nt100), (Pt100,Nt100), (N100,Nt100),(N100,Pt100), (P100,Pt100,N100), (P100,Pt100,Nt100), (Pt100,N100,Nt100), (P100,N100,Nt100) and (P100,Pt100,N100,Nt100). The classification accuracy at F3 electrode for 11 attribute combinations is shown in Table 2.

Table 2:Classification accuracy atF3 electrode for 11 attributes combinations

Subjects	**Classification accuracy atF3 electrode for 11attribute combinations**										
	P100-Pt100 (%)	P100-N100 (%)	P100-Nt100 (%)	Pt100-Nt100 (%)	N100-Nt100 (%)	N100-Pt100 (%)	P100-Pt100-N100 (%)	P100-Pt100-Nt100 (%)	Pt100-N100-Nt100 (%)	P100-N100-Nt100 (%)	P100-Pt100-N100-Nt100 (%)
Subject 1	52.63	57.89	68.42	57.89	63.15	57.89	73.68	73.68	57.89	52.63	73.68
Subject 2	62.5	54.16	66.66	62.5	58.3	70.8	66.66	62.5	66.66	58.3	66.66
Subject 3	58.33	63.5	66.66	68.32	62.5	58.33	54.16	70.8	66.66	62.5	62.5
Subject 4	53.84	46.15	53.84	59.83	63.33	57.69	57.69	61.5	53.8	57.6	73.07
Subject 5	66.66	57.14	61.90	61.90	66.66	76.19	66.66	61.90	66.66	57.80	76.19

It can be seen from table2that atF3 electrode for different attribute combinations, the best accuracy of 73.68% has been achieved for attribute combinations(P100, Pt100, N100, Nt100), (P100, Pt100, N100) and (P100, Pt100, Nt100) in case of subject 1. In the same way for subject 2, the best accuracy of 70.80% has been obtained for attribute combination (N100, Pt100). For subject 3, the best accuracy achieved for attribute combination (P100, Pt100, Nt100)is 70.8% and for subject 4, an accuracy of 73.07% has been achieved for attribute combination(P100, Pt100, N100, Nt100). In the same way, for attribute combination (P100, Pt100, N100, Nt100), (N100, Pt100), the best accuracy of 76.19% has been obtainedfor subject 5. The classification accuracy at F4 electrode for 11 attribute combinations is shown in Table 3.

Table 3:Classification accuracy at F4 electrode for 11attributes combinations

Subjects	**Classification accuracy at F4 electrode for 11 attributes combinations**										
	P100-Pt100 (%)	P100-N100 (%)	P100-Nt100 (%)	Pt100-Nt100 (%)	N100-Nt100 (%)	N100-Pt100 (%)	P100-Pt100-N100 (%)	P100-Pt100-Nt100 (%)	Pt100-N100-Nt100 (%)	P100-N100-Nt100 (%)	P100-Pt100-N100-Nt100 (%)
Subject 1	57.8	57.89	66.66	67.89	63.15	68.4	57.8	52.6	63.15	63.15	57.8
Subject 2	62.5	66.66	79.16	62.5	62.5	54.16	75	62.56	66.66	75	66.66
Subject 3	62.5	70.88	62.5	70.83	58.33	75	62.66	66.66	68.26	62.5	66.66
Subject 4	76.92	69.23	65.38	65.38	61.5	65.38	57.69	65.38	61.5	69.23	72.03
Subject 5	66.66	61.90	71.4	57.14	71.42	66.66	61.9	57.14	61.9	57.14	64.15

The best accuracy has been achievedalong attribute combination(N100, Pt100)is 68.4% for subject 1. For subject 2, the highest accuracy of 79.16% has been obtained for attribute combination (P100, Nt100). In the same way, the best accuracy achieved for attribute combination (N100, Pt100)is 75% for subject 3. The best accuracy of 76.92% has been obtained in case of subject 4 for attribute combination (P100, Pt100). In case of subject 5, an accuracy of 71.42% has been achieved for attribute combination (P100, Nt100) and (N100, Nt100). The classification accuracy at Fz electrode for 11 attribute combinations is shown in Table 4

Table 4:Classification accuracy at Fz electrode for 11 attributes combinations

Subjects	**Classification accuracy at Fz electrode for 11attribute combinations**										
	P100-Pt100 (%)	P100-N100 (%)	P100-Nt100 (%)	Pt100-Nt100 (%)	N100-Nt100 (%)	N100-Pt100 (%)	P100-Pt100-N100 (%)	P100-Pt100-Nt100 (%)	Pt100-N100-Nt100 (%)	P100-N100-Nt100 (%)	P100-Pt100-N100-Nt100 (%)
Subject 1	52.63	52.63	68.42	57.89	63.15	57.89	63.15	63.15	63.15	57.89	57.8
Subject 2	62.5	58.33	62.5	62.5	66.66	58.33	62.5	70.83	62.5	66.66	62.5
Subject 3	62.5	70.88	58.33	62.5	66.66	58.33	61.5	62.5	66.66	58.3	70.8
Subject 4	61.5	57.89	65.38	73.07	69.23	53.28	57.69	65.38	57.89	61.5	61.5
Subject 5	71.42	61.90	66.66	66.66	61.9	71.42	71.42	57.14	61.9	57.14	61.9

The best accuracy of 68.42% has been achieved for attribute combination(P100, Nt100) in case of subject 1. In the same way for subject 2, the accuracy of 70.83% has been obtained for attribute combination (P100, Pt100, Nt100). For subject 3 the best accuracy achieved for attribute combination (P100, Pt100, N100, Nt100) and (P100,N100)is 70.80%. An accuracy of 73.07% has been obtained for attribute combination (Pt100, Nt100) in case of subject 4. In the same way for subject 5, the accuracy obtained for attribute combination of (P100, Pt100), (N100, Pt100) and (P100, Pt100, N100)is 71.42%. When average of 11 different attribute combination extracted from four attributes is performed, the best accuracy obtained is shown in Figure 4.

Comparison for 11 attribute combinations

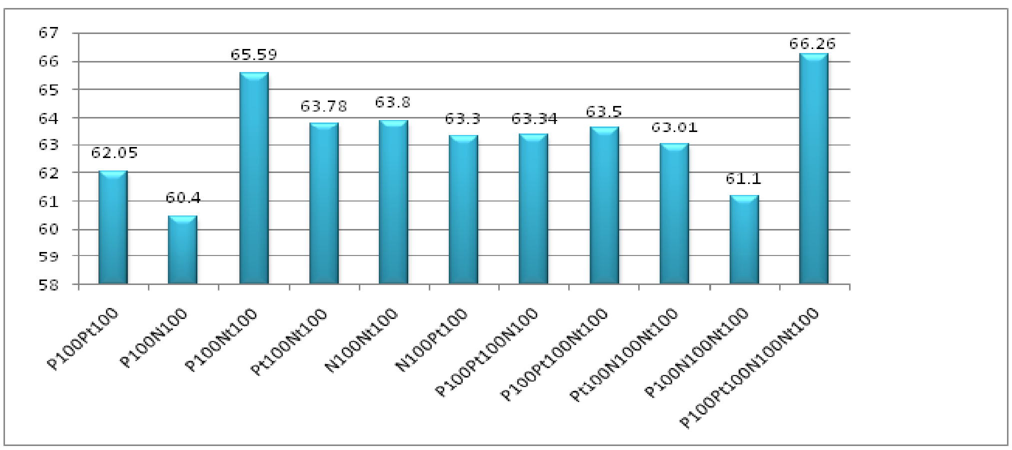

Figure 4:Classification accuracy of 11 attributes combinations

It can be seen that the best accuracy hasbeenobtained for (P100, Pt100,N100,Nt100) followed by (P100, Nt100) and (N100, Nt100). An accuracy of 66.26% has been achieved for (P100,Pt100,N100,Nt100), 65.59% for (P100, Nt100), 63.89% for (N100, Nt100).

It shows that for the ERP attributes P100, N100, Pt100 and Nt100; theattribute combination (P100, Pt100, N100, Nt100)comes out to be the best parameter for classifying emotions along the arousal axis.

6. Conclusion

In this paper, we extracted ERP attributes from the acquired EEG signalfor classification of emotions into two classes along the arousal axis.Among the eleven attribute combinations used in this study, (P100,Pt100,N100,Nt100)is found to be the best combination as accuracy remained consistently high for this combination on all electrodes. The average classification accuracy with this combination comes out to be 66.26%. It is further noticed that by reducing the number of attributes, the classification accuracy decreases. However if we take (P100, Nt100) the classification accuracy is 65.59% which is marginally lower. Hence we may go in for this combination as well if computational time is restricted.

7. Scope for Future Work

Since the emotions areclassified under laboratory conditions, it is impossible to know the exact instance at which emotions has been evoked which is in fact a drawback. Furthermore only four attributes such as P100, Pt100, N100 and Nt100areextracted for emotion classification.By considering more number of ERPfeaturesand subjects, the scope could be widened.

References

[1] T. Ahmed, M. Islamand M. Ahmad“Human Emotion Modeling Based on Salient Global features of EEG Signal” Proceedings of 2013 2nd International Conference on Advances in Electrical Engineering , pp. 19-21, Dec 2013

[2] R. Plutchik, “The Emotions: Facts, Theories and a New Model”, Random House, New York, 1962

[3] P. Ekman, W.V. Friesen, M. O’Sullivan, A. Chan, I. Diacoyanni-Tarlatzis, K. Heider, R. Krause, W.A. LeCompte, T. Pitcairn, and P.E. Ricci-Bitti, “Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion,” J. Personality and Social Psychology, vol. 53, no. 4, pp. 712-717, Oct 1987

[4] Mandeep Singh,“Introduction to biomedical Instrumentation”, PHI Learning Pvt. Ltd, New Delhi, 2010

[5] J.A.Russell, “A Circumflex Model of Affect.” Journal of Personality and Social Psychology, vol.39, pp.1161-1178, 1980

[6] M.M.Bradley and P.J.Lang “Measuring emotions: The self assement manikin and the semantic differential” Journal of behavior therapy and experimental psychiarty, vol. 25,pp.49-59,March 1994

[7] R.W. Picard, E. Vyzas and J.Healey“Toward machine emotional intelligence: analysis of affective physiological state” IEEE Transaction on pattern analysis and machine intelligence, Vol. 23, pp. 10, October 2001

[8] G.Chanel, K.Ansari.Asl, and T. Pun “Valence-arousal evaluation using physiological signals in an emotion recall paradigm” IEEE 2007

[9] 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” .IEEE Computer society,vol.2issue1 pp. 18-31,Doi http://doi.ieeecomputersociety.org/10.1109/T-AFFC.2011.15,jan-march 2012

[10] R.Horlings,D.Datcu, and L.J.M.Rothkrantz."Emotion recognition using brain activity." Proceedings of the 9th international conference on computer systems and technologies and workshop for PhD students in computing. ACM, 2008

[11] M.Murugappan, R.Nagarajan, and S.Yaacob “Comparison of Different Wavelet Features from EEG Signals for Classifying Human Emotions” IEEE Symposium on Industrial Electronics and Applications, vol. 2, pp. 836-841, 2009

[12] M. M, Bradley andP. J. Lang “The International Affective Picture System (IAPS) in the Study of Emotion and Attention”, Handbook of Emotion Elicitation and Assessment, Oxford University Press, 2007

[13] C. A. Frantzidis, C. Bratsas, C. L Papadelis, E. Konstantinidis, C. Pappas andP.D. Bamidis, “Toward emotion aware computing: An integrated approach using multichannel neurophysiological recordings and affective visual stimuli”. IEEE Transactions on Information Technology In Biomedicine vol.14, pp.589-597, 2010

[14] R.Khosrowabadi, H.C.Quek and A.Wahab “EEG-based emotion recognition using self-organizing map for boundary detection” 20th International Conference on Pattern Recognition,pp.4242-4245, 2010

[15] H.Xu, K.N.Plataniotis “Affect Recognition Using EEG Signal” IEEE 14th International Workshop on Multimedia Signal Processing, pp. 299-304, 2012

[16]Mandeep Singh, Mooninder Singh and Nikhil Singhal“Emotion Recognition along valence Axis Using naïve bayes Classifier”International Journal of Information Technology & Knowledge Management, vol. 7,no.1, pp.51-55, Dec 2013

[17] Mandeep Singh, Mooninder Singh and Nikhil Singhal“ANN Based Emotion Recognition Along Valence Axis Using EEG”, International Journal of Information Technology & Knowledge Management, vol.7no.1,pp.56-60, Dec 2013

[18] Mandeep Singh, Mooninder Singh and Nikhil Singhal“Emotion Quantification along Valence Axis Using EEG Signals”, International Journal of Information Technology & Knowledge Management, vol.7, no.1, Dec 2013

[19] Mandeep Singh, Mooninder Singh and Surbhi Gangwar “Feature Extraction from EEG for Emotion Classification” International Journal of Information Technology & Knowledge Management, vol.7, no.1, pp.6-10, Dec 2013

[20] Mandeep Singh, Mooninder Singh and Surbhi Gangwar “Arousal Detection Using EEG Signal” International Journal of Information Technology & Knowledge Management, vol.7, no.1,pp.11-15, Dec 2013

[21] Mandeep Singh, Mooninder Singh and AnkitaSandel“Emotion Classification along Valence Axis Using ERP Signals” International Journal of Information Technology & Knowledge Management,vol. 7, no. 2, pp. 143-152, June 2014

[22] Mandeep Singh, Mooninder Singh and AnkitaSandel“Emotion Classification along Valence Axis Using Averaged ERP Signals” International Journal of Information Technology & Knowledge Management, vol. 7, no. 2, pp. 153-161, June 2014

[23] MP Hardware guide available at http://www.biopac.com/Manuals/mp_hardware_guide.pdf

[24] Mandeep Singh, Mooninder Singh and AnkitaSandel “Data Acquisition Technique for EEG based Emotion Classification” International Journal of Information Technology & Knowledge Management, vol. 7, no. 2, pp. 133-142, June 2014

[25] Acqknowledge 4 software guide, available at
http://www.biopac.com/Manuals/acqknowledge%204%20software%20guide.pdf

[26]Chang, Chih-chung, Lin, Chih-Jen. “LIBSVM: A library for support vector machines”Internet: www.csie.ntu.edu..tw/~cjlin/libsvm/ ,2011