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Emotion classification using EEG Entropy

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: Human emotions can be expressed as a state of mind which can predict the response of a person whether positive or negativeto a particular stimulus. In this paper, the aim of the project is to design an interactive and a smart system for emotion recognition based on Electroencephalogram (EEG) signals. EEG signals are acquired from three subjects on two frontal electrodes namely F3 and F4 for classification of emotions into two classes. The stimulus to subjects is providedby images from International Affective Picture System (IAPS).The EEG data isdecomposed into five different frequency bands namely delta (0-4 Hz), theta (4–8 Hz), alpha (8–16 Hz), beta (16–32 Hz) and gamma (32- 64Hz) by using filtering technique. The entropy attribute has been extractedfor every class of emotionsfrom the five frequency bands.The training and testing is performed on six combinations of the Entropy attribute extracted from the different frequency bands. The classification of emotions is performed using LIBSVM(3 fold cross validation)with RBF kernel.When emotions are classified subject wise, ithas beenfound that accuracy remains consistently high whenthe combination of entropies extracted from all five frequency bands has been used for classification. The maximum accuracy of 68.50% has been achievedonF3 electrode and 66.66% onF4 electrode.

Keywords: Emotions, Entropy, LIBSVM.

1. Introduction

Emotions play a central role in our interaction with outside world. It can be defined as a psychological state of mind that occurs unexpectedly by an individual [1].In our everyday activities, such as social communication and decision making tasks are highly affected by people's moods and different emotional states.Different models on emotions werespecified by researchers. The first model was specified by Darwin which was further carry on by Plutchik and Ekman.Plutchikconsidered that emotions such as curiosity, disgust, joy, surprise, anger, joy, fear, acceptance, and sadness are eight basic emotions [2]. Whereas Ekman considered thatemotions namely fear, happiness, anger, disgust, sadness and surprisearesix basic feeling of human being [3].There are more than 90 definitions of "emotion" and there is little consent on the meaning of the term [4].Without the emotion identification, even the personwho is rigorously suffering from stroke, paralysis, Amyotrophic lateral sclerosis (ALS) and other brain related disorders may lose their ability to speak or to communicate with environment[5]. Sothis necessitatesdesigningan affective emotion classifier. For example, driver of bus driving on road in a bad moodis not only risky to himself but also to other traveler in the same bus.Many researchers give literature on recognition of emotions based on facial expression, speech and gesture of human being but these features results into inaccurate emotional states. So emotion recognition from physiological signals such as Blood Volume Pulse (BVP), Electrocardiogram (ECG), Galvanic Skin Response (GSR) and Electroencephalogram (EEG) is important for the study of emotions [6]. As EEG signals can also be used for detecting epileptic activity of brain through which emotions can be recognized of epileptic person[7].Russell, J.A. (1980) projected a circumflex model of affect in which emotions were demonstrated in a two dimensional space. According to his approach pleased was characterizing the x-axis and unpleased was characterizing along y-axis. The emotion describing words were so arranged that the like meaning words were closer while the opposites was arranged diagonally [8]. Later this model was enhanced by Lang et al where the two dimensions were differentiated by valence and arousal [9].
Some basic emotions namely happy, sad, surprised, angry, excited, frustrated, calm, shocked and naughty which can be seen in our daily routine shown in Figure 1.

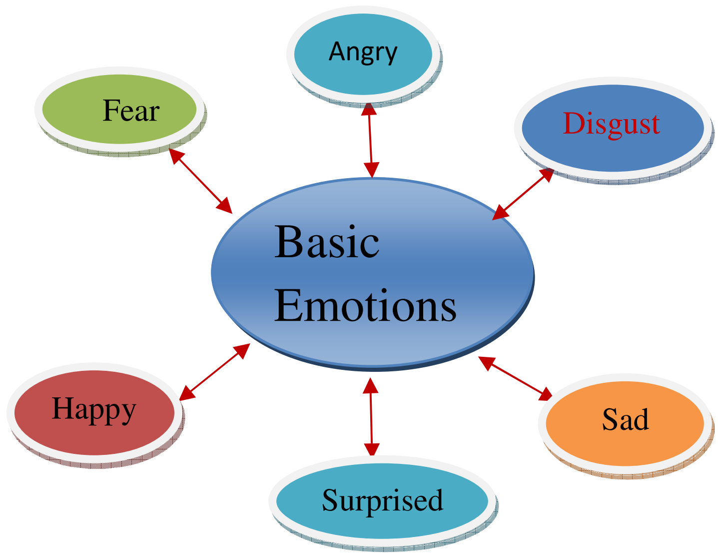

Figure 1: Basic Emotions

2. Review

Kim, K.H*et al.* (2004) collected physiological database such as electrocardiogram and skin temperature variations from fifty participants. The emotions were classified into four emotional states namely sad, anger, stress, surprise to build a user-independent system for recognizing emotions. The classification was performed by support vector machine as pattern classifier with ratios obtained was 78% and 61.8% in case of three and four distinct emotions respectively [10].Murugappan, M *et al*. (2009) acquired EEG data when stimulated by audio-visual stimuli from 20 healthy subjects. The classification of emotions was done into five classes such as disgust, happy, surprise, fear and neutral. Using wavelet transforms, the EEG signal was decomposed into five different frequency bands (delta, theta, alpha, beta and gamma). Through the use of 5 fold cross validation withLinear discriminate analysis (LDA) & K Nearest neighbor (KNN) classifier, classification was performed. An average accuracy of 79.14% was obtainedwith maximum subset emotion rate of 73.75% on fear, 91% on disgust, 60% on surprise,88% on happy, and 87.5 % on neutral emotions was achieved[11]. Petrantonakis, P.C*et al.* (2010) collected EEG data from sixteen healthy subjects from three EEG channels, namely Fp1, Fp2 and a bipolar channel of F3 and F4 according to position of international 10–20 system. The emotions were classified into six basic emotions states namely happiness, surprise, anger, fear, disgust, and sadness when novel emotion elicitation method based on the Mirror Neuron System was used to promote emotion stimulation. The extracted features using higher order crossings (HOC) were classified with four different classifiers namely quadratic discriminant analysis (QDA), *k*-nearest neighbor, Mahalanobis distance and support vector machines (SVMs) for recognition of emotions. The EEG data examined from single-channel and from combined-channels results in accuracy of 62.3% using QDA and 83.33% using SVM respectively [12].

Anh, V.H*et al.* (2012) collected EEG data when images from IAPS dataset were used for evoking emotions [13]. Two approaches from Russell's circumplex model were used. The algorithm used was Higuchi Fractal Dimension with Support Vector Machine as classifier. First approach was machine learning in which EEG signals of all the participants were taken under consideration and second approach was the machine learning in which EEG signal of individual participants were taken. Since EEG signal of every subject has different characteristic so results showed that first approach was impossible to apply but second approach of individual subjects under consideration was used and can recognize five states of human emotion average accuracy 70.5% [14]. The IAPS dataset for evoking of emotions has been used by number of other researchers for recognition of emotions and different attributes such as event related potential and average of event related potential. The classification was done using support vector machines as classifier [15-16].

Singh, M. *et al.* (2013) used the eNTERFACE 06 EEG database for classifying emotions into two classes [17]. Different attributes such as Power Spectral Density (PSD), Short Time Fourier Transform (STFT), event Related Potential (ERP), power, Entropy and varianceon 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 [18-22].

Murugappan, M. *et al.*(2013) acquired EEG data when stimulated by audio-visual stimuli from 20 healthy subjects. The emotion was performed into five classes such as disgust, happy, surprise, fear and neutral.The attributes extracted was spectral centroid and spectral entropy when EEG data was decomposed into four frequency bands namely alpha (8 Hz - 16 Hz), beta (16 Hz - 32 Hz), gamma (32 Hz - 60Hz) and alpha to gamma (8 Hz - 60 Hz) using Fast Fourier Transform (FFT). The classification was carried out using k-Nearest Neighbor (KNN) and Probabilistic Neural Network (PNN). The highest accuracy of 91.33% on beta band was obtained which was indicating that KNN classifier was perform better than PNNclassifier [23].

3. Data acquisition

For classification of emotions, EEG data is acquired from three healthy male subjects with normal to corrected vision and have no health issue. The hardware used for capturing brain signals isBIOPAC data acquisition unit MP150interfaced with EEG cap. EEG cap has total of 20 electrodes as per International 10-20 system that can be used in unipolar or biopolar [24]. EEG cap is placed over the head of participant whose data is to capture. Only two frontal electrodes namely F3 and F4are used for classification. The images from International Affective Picture System (IAPS) provided by national institute of mental health centre of emotions (NIMH) are used as stimuli for evoking emotions of participants. These images were collected by the scientist of university of Florida. The images shown to subjectsare corresponding to High Valence High Arousal and High Valence Low Arousal. The systemused for acquiring EEG signal iscomposed of EEG amplifiers, EEG gel used in electrode, earlobes attached to the participants. To make contact between electrodes, EEG gel is used in the electrodes. First images shown to subject is corresponding to High Valence High Arousal for a period of 1second followed by plus symbol with a black background for a period of 1.5 second. With suitable coordination between the data acquisition system and display system of images, EEG data has been collected at sampling rate of 500 samples per second [25].

The methodology followed for acquisition and classification of emotions was as shown in Figure 2.

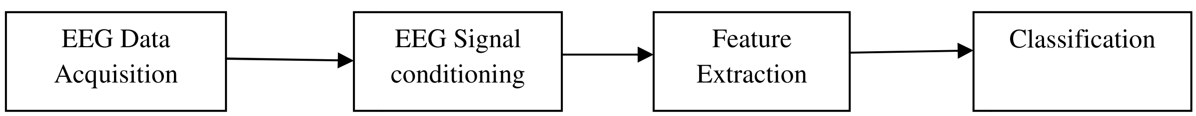

Figure 2: Methodologyused for classification of emotions

4. Hardware

To capture EEG signal from human being for classification of emotion, there can be too many ways. One method used by Savran et al. (2006) was functional Near Infrared Spectroscopy (fNIRS) sensor to capture frontal brain activity, to capture activity in the rest of the brain and for acquiring peripheral body processes such as respiration belt,a plethysmograph (blood volume pressure) and GSR (Galvanic Skin Response) [17]. In this BIOPACdata acquisition unit MP150is used which is a computer based acquisition system. The MP system namely MP150 or MP100 is a heart of data acquisition system. This MP150 unit takes incoming signals and converts this incoming signal into digital signal whichis processed by computer. This processed signal is displayed on screen and stored in memory of computer which can be used for further examination [26].

5. Conditioning of EEG signal

After the acquisition of EEG signal, conditioning of signal is very important aspect for obtaining better classification results. The acquired EEG signal is preprocessed for removal of any interference.This interference may be due to blink of eyes or any body movement of participants under concern. The signal ispreprocessed in offline mode by using ACQ4.2 Software provided by BIOPAC [27].The signal is filtered through low pass IIR filter with cut off frequency of 40 Hz and high pass IIR filter with cut off frequency of 0.5 Hz. The noise interference is removed by comb band pass filter with notch frequency of 50 Hz. Figure 3 to 6shows filtering operations step by step as shown:

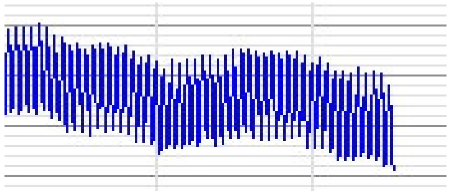
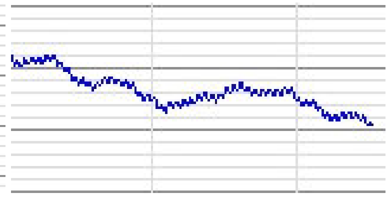

Figure 3:Before preprocessing of signal Figure 4: Low pass IIR filter

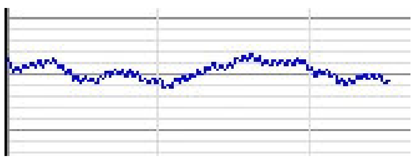
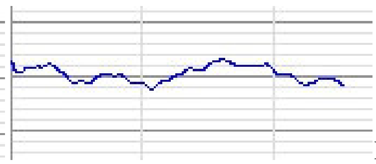

Figure 5:High passIIR filter Figure 6: Comb band stop filter

6. Feature extraction

The preprocessed EEG data has been usedforattribute extraction. EEG spectrum contains some characteristic waveforms that fall primarily with five frequency bands. Different researches give different ways to work on these bands, the bands chosen lies in the following frequency manner: delta (0-4 Hz), theta (4–8 Hz), alpha (8–16 Hz), beta (16–32 Hz) and gamma (32- 64Hz). Feature extracted from these five frequency bands of EEG signal is Entropy. It is considered as the strongest feature for emotion classification and defined as degree of randomness of signal [28].
EEG preprocessed signal with fivefrequency bands as shown in Figure 7 to 12.

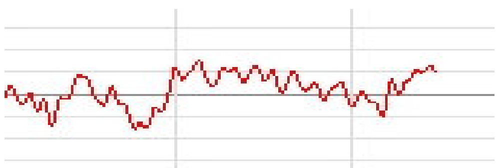
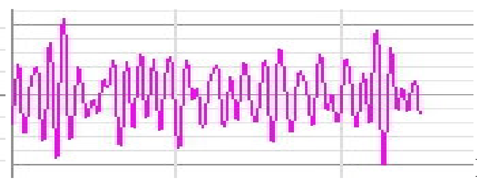

Figure 7:Preprocessed EEG signal Figure 8:Gamma band


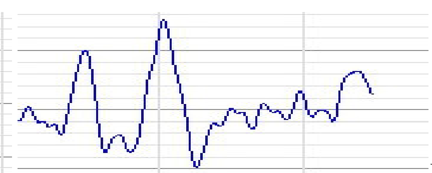

Figure 9:Deltaband Figure 10:Theta band

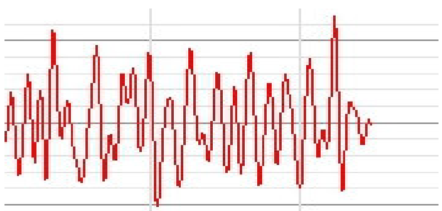


Figure 11:Beta bandFigure 12:Alpha band

7. Results and Discussion

The classification has been done into two classes' namely high Valence High Arousal and High Valence Low Arousal.Theclassification has beencarried out subject wise using LIBSVM (3 fold cross validation)withRBF kernel for classification of emotions along arousal axis [29].The training and testing has been carried out separately for each subject from five decomposed bands of EEG signal. For training,70% of the samples have been used and the remaining 30% of the samples has been used for testing. The best values of cost factor and gamma is calculatedby training the model for every subject. Using this best model, testing has been performed on the test dataset of that subject. The classification has been carried out on six combinations of the five sub bands such as delta, theta, alpha, beta, gamma of EEG signal.The classification accuracy at F3 and F4 electrode for subject 1 is shown in Table 1.

Table1:Classification accuracy at F3 and F4 electrode for subject 1:

Subject 1		
Entropy combination	**Accuracy atF3 electrode (%)**	**Accuracy atF4 electrode (%)**
E_d E_t $E_aE_bE_g$	62.5	58.89
E_d E_t E_aE_b	58.33	46.77
E_t $E_aE_bE_g$	54.16	58.33
E_d $E_aE_bE_g$	58.88	58.88
E_d E_t E_aE_g	45.83	57.14
E_d E_t E_bE_g	41.88	45.38

It can be seen for subject 1, when taking all entropy combinationsacquired by decomposing an EEG signal into five frequency bands, an accuracy of 62.5% has been obtained for F3 electrode and 58.89% for F4 electrode. In the same way when entropy determined by taking alpha beta theta delta combinations of EEG signal, an accuracy of 58.33% has been obtained for F3 electrode, 46.77% for F4 electrode. An accuracy of 54.16 has been obtained for F3 electrode and 58.33% for F4 electrode when entropy combination such as alpha beta theta gamma is taken under observation. For the entropy combination namely alpha beta delta gamma of EEG signal, an accuracy of 58.88% has been achieved for F3 and F4 electrode. In the same way an accuracy of 45.83% for F3 electrode and 57.14% for F4 electrodehas been achievedwhen entropy is determined by taking alpha theta delta gamma combination of EEG signals. When entropy combination such as beta theta delta gamma of EEG signal is taken, an accuracy of 41.88% for F3 electrode and 45.38% for F4 electrode has been obtained.
From Figure 13 it can be seen that the best results are obtained when considering all five frequencybands of EEG signal for subject1.

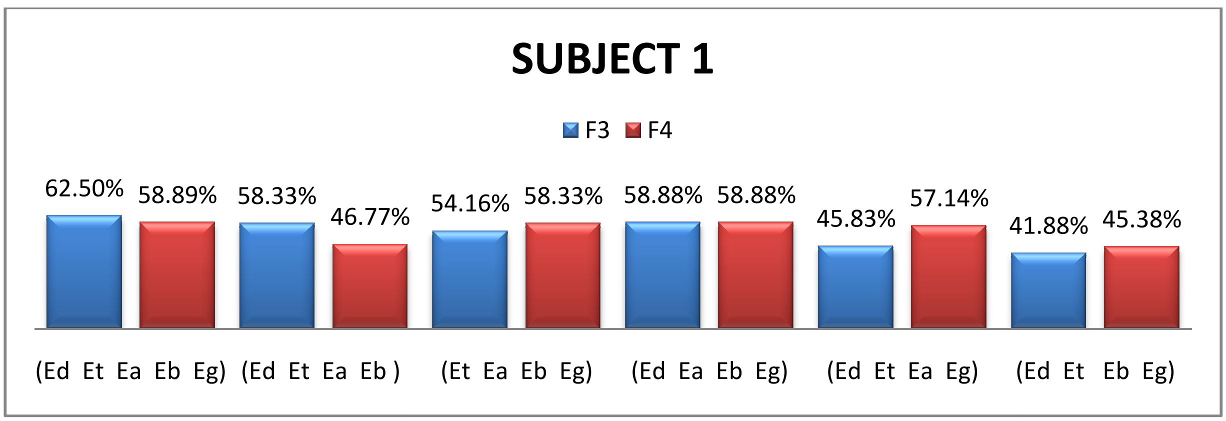

Figure 13:Classification accuracy of Subject 1 for different Entropycombinations

In the same way for subject 2, the best accuracy of 63.42% has been achievedfor F3 and 66.66% for F4 electrode when all entropy combinations acquired by decomposing an EEG signal into five frequency bands areconsidered. The classification accuracy at F3 and F4 electrode for subject 2 is shown in Table 2.

Table2:Classification accuracy at F3 and F4 electrode for subject 2:

Subject 2		
Entropy combination	**Accuracy atF3 electrode (%)**	**Accuracy atF4 electrode (%)**
E_d E_t $E_aE_bE_g$	63.42	66.66
E_d E_t E_aE_b	61.9	52.38
E_t $E_aE_bE_g$	66.66	57.14
E_d $E_aE_bE_g$	57.42	57.14
E_d E_t E_aE_g	61.90	61.9
E_d E_t E_bE_g	59.89	41.38

From Figure 14 it can be seen that the best results are obtained when considering all five frequency bands of EEG signal for subject2.

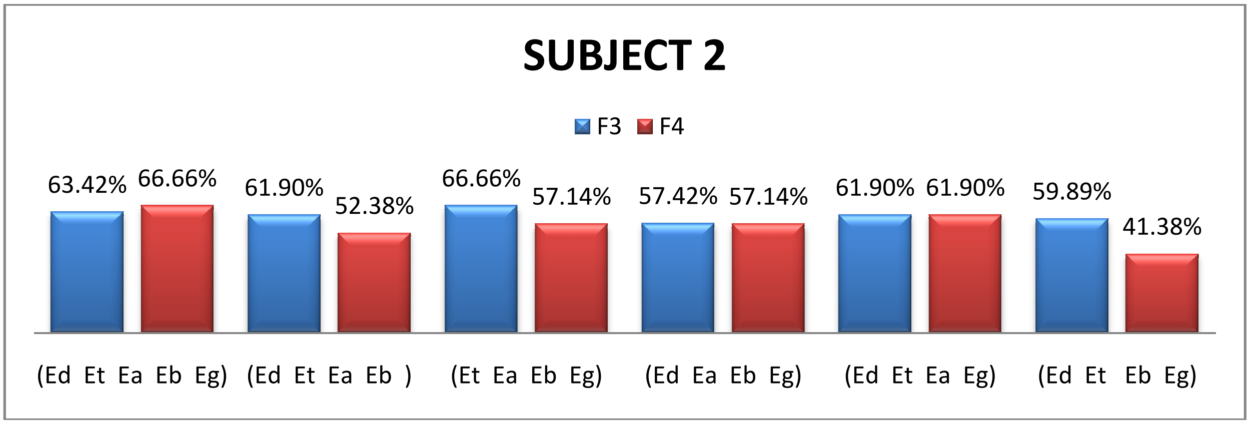

Figure 14:Classificationaccuracy of Subject 2 for different Entropycombinations

For subject 3, better results has been obtained by taking all band combinations with highest accuracy achieved up to 68.5% for F3 electrode and 66.66% for F4 electrode. The classification accuracy at F3 and F4 electrode for subject 3 is shown in Table 3.

Table3:Classification accuracy at F3 and F4 electrode for subject 3:

Subject 3		
Entropy combination	**Accuracy atF3 electrode (%)**	**Accuracy at F4 electrode (%)**
E_d E_t $E_aE_bE_g$	68.5	66.66
E_d E_t E_aE_b	54.16	52.38
E_t $E_aE_bE_g$	45.83	57.14
E_d $E_aE_bE_g$	57.14	57.14
E_d E_t E_aE_g	61.90	45.38
E_d E_t E_bE_g	41.88	61.9

From Figure 15 it can be seen that the best results are obtained when considering all five bands of EEG signal for subject3.

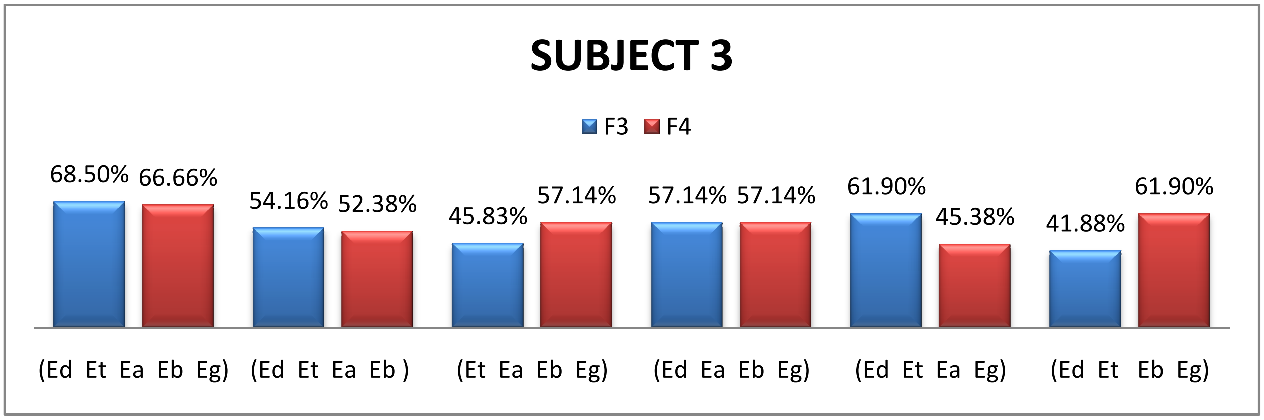

Figure 15:Classification accuracy of Subject 3 for different Entropy combinations

It can be seenfrom Figure 16 when all fivefrequency bands of EEG signal are compared for every subject along F3 and F4 electrode, the accuracy is remainingin the range nearly 60% to 70%. The highest accuracy has been obtained along F3 electrode followed by F4 electrode as shown in Figure16. An accuracy of 68.50% has been achieved along F3 electrode,66.66% forF4 electrode.

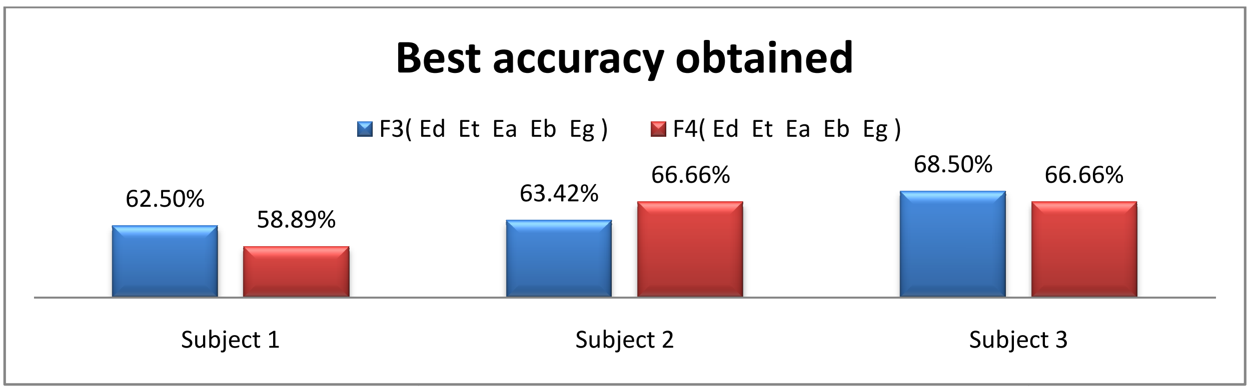

Figure 16: Best classificationaccuracy obtained Subject wise

It shows that classification of emotions along the arousal can be performed best when combination of entropies extracted from all five frequency bands are used for classification.

8. Conclusion

In thisstudy, we extracted Entropy attributes from five frequency bands of EEG signal for classification of emotions along arousal axis into two classes. Among the six combinations used in this study, E_d $E_tE_aE_bE_g$has been found to be the best combination. The accuracy of classification along arousal axis achieved is 68.50% at F3 electrode and 66.66% at F4 electrode when all five frequency bands of EEG signal are considered.

9. Scope for Future Work

The emotion classifier designed in this study is subjective one not universal. It requires repetition of whole procedure for every subject which is actually a shortcoming. In addition to these only two electrodes are used for classification, so scope could be widened by increasing the number of electrodes.

References

[1] Emotions, available at http://www.thefreedictionary.com/emotion

[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]Robert Horlings, “Emotion recognition using brain activity”, Man-Machine Interaction Group TU Delft 27 March 2008

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

[6] R. W. Picard, Affective Computing: MIT Press, 1997

[7] Mandeep Singh and SunpreetKaur “Epilepsy Detectionusing EEG anoverview” International Journal of Information Technology and Knowledge Management, vol.6, no.1, pp.3-5, Dec 2102

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

[9] 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

[10] K.H. Kim, S.W. Bang, S.R. Kim "Emotion recognition system using short-term monitoring of physiological signals." Medical and biological engineering and computing, vol. 42, pp.419-427, 2004

[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] P.C.Petrantonakis and L.J.Hadjileontiadis. "Emotion recognition from EEG using higher order crossings" IEEE Transactions on information Technology in Biomedicine, vol.14, Issue.2 pp. 186-197, 2010

[13] M. M, Bradley and P. 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

[14] V.H.Anh, M.N.Van, B.B.Ha and T.H.Quyet"A real-time model based support vector machine for emotion recognition through EEG", IEEE International Conference onControl, Automation and Information Sciences, pp.191-196, 2012

[15] 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

[16] 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

[17] 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.2issue1 pp. 18-31,Doi http://doi.ieeecomputersociety.org/10.1109/T-AFFC.2011.15,jan-march 2012

[18]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

[19] 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

[20] 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

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

[22] 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

[23] M.Murugappan and S.Murugappan “Human Emotion Recognition through Short time Electroencephalogram (EEG) Signals Using Fast Fourier Transform (FFT)” 9th IEEE International Colloquium on.SignalProcessing and its Applications, 2013

[24]V.Jurcak, D.Tsuzuki and I.Dan, “10.20, 10/10 and 10/5 systems revisited, their validity as relative head surface based positioning systems” Neuro image, vol. 34, Issue. 4, pp.1600-1611, 2007

[25] Mandeep Singh, Mooninder Singh and Money Goyal“Selection of attribute combinations of ERP’s for classification of emotions along arousal axis”International Journal of Information Technology & Knowledge Management,vol.8, no.2, 2015

[26] MP system hardware available at http://www.biopac.com/manuals/mp_hardware_guide.pdf

[27] Acqknowledge 4 software guide, available at,http://www.biopac.com /Manuals/acqknowledge%204%20software%20guide.pdf, pp.31-95

[28]Mandeep Singh and HarleenKaur “ANN based Epilepsy detection using EEG” International Journal of Information Technology & Knowledge Management, vol.7, no.1, pp.31-40, Dec 2013

[29]Chang, Chih-chung, Lin, Chih-Jen. “LIBSVM: A library for support vector machines”Internet: www.csie.ntu.edu..tw/~cjlin/libsvm/ ,2011 [June13,2015]