Human Emotion Recognition Through Short Time Electroencephalogram (EEG) Signals Using Fast Fourier Transform (FFT)

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Abstract: *Human emotion recognition plays a vital role in psychology, psycho-physiology and human machine interface (HMI) design. Electroencephalogram (EEG) reflects the internal emotional state changes of the subject compared to other conventional methods (face recognition, gestures, speech, etc). In this work, EEG signals are collected using 62 channels from 20 subjects in the age group of 21~39 years for determining discrete emotions. Audio-visual stimuli (video clips) is used for inducing five different emotions (happy, surprise, fear, disgust, neutral). EEG signals are preprocessed through Butterworth 4th order filter with a cut off frequency of 0.5 Hz - 60 Hz and smoothened using Surface Laplacian filter. EEG signals are framed into a short time duration of 5s and two statistical features (spectral centroid and spectral entropy) in four frequency bands namely alpha (8 Hz - 16 Hz), beta (16 Hz - 32 Hz), gamma (32 Hz - 60 Hz) and alpha to gamma (8 Hz - 60 Hz) are extracted using Fast Fourier Transform (FFT) . These features are mapped into the corresponding emotions using two simple classifiers such as K Nearest Neighbor(KNN) and Probabilistic Neural Network (PNN). In this work, KNN outperforms PNN by offering the maximum mean classification accuracy of 91.33 % on beta band. This experimental results indicates the short time duration of EEG signals is highly essential for detecting the emotional state changes of the subjects.*

Keywords: Electroencephalogram (EEG), Fast Fourier Transform (FFT), K Nearest Neighbor (KNN), Probabilistic Neural Network (PNN)

I. INTRODUCTION

Emotion is one of the most important features of humans. Identifying the emotional changes from EEG signals has recently gained attention among Brain Computer Interface (BCI) researchers for developing different BCI devices. Emotion is one of the key factors that used to understand the mental behavior of the human. Recent years, assessing emotional state changes of the patients under psychological/psycho-physiological counseling can be easily done through EEG signals in contrast with other conventional methods such as speech, gestures, facial expression, etc [1, 2]. Since, EEG signals are directly connected to the scalp and reading the onset changes in brain activity to give more reliable information about the emotional state changes. In addition, this emotional assessment concept is also been explored majorly in human robot interactions for developing assisting device for elder peoples. Although limited in number compared with the efforts being made towards intention-translation means, some researchers are trying to realize man-machine interfaces with an emotion understanding capability. The traditional tools for the investigation of human emotional status are based on the recording and statistical analysis of physiological signals from the both central and autonomic nervous systems (CNS and ANS). Several approaches have been reported by different researchers on finding the correlation between the emotional changes and EEG signals [3-5]. The comprehensive studies on emotion recognition using physiological signals is reported in [6]. In emotion assessment using EEG signals, the time duration of EEG signals under given emotional stimuli, number of channels, frequency bands, nature of statistical feature extraction methods and features plays an significant role. However, most of the earlier works have not analyzed the short time EEG signals in contrast with longer duration for emotion recognition. Indeed, alpha (8 Hz - 16 Hz), beta (16 Hz - 32 Hz), gamma (32 Hz - 60 Hz). In this research domain, selecting appropriate frequency bands, characterizing non-linearity of EEG signals, and selection of most efficient emotion induction stimuli are the major challenges. Still the researchers are addressing the above issues through different signal processing methods and the results do not guarantee the very good recognition rate (above 90%).

In this work, audio-visual stimuli (video clips) is used for evoking five different emotions such as disgust, happy, fear, surprise and neutral. Two statistical features (spectral entropy and spectral centroid) have been derived using Fast Fourier Transform (FFT) over four different frequency ranges (alpha, beta, gamma and alpha to gamma). These numerical features are classified into discrete emotions using two different classifiers namely K Nearest Neighbor (KNN) and Probabilistic Neural Network (PNN). The main objective of this work to analyze the short time EEG signals (5s) to enhance the emotion assessment rate through a set of simple statistical features. In addition, the results of this work also discusses about the impact of containing more useful emotional state information in different frequency bands of EEG signals. Lastly, the classification rate of discrete emotions on two different features over four frequency bands are compared by using two simple classifiers. The basic research methodology on human emotion recognition is shown in Figure 1.

The rest of this paper is organized as follows. Section II discuss about the summarization of the research methodology by elucidating the data acquisition process, preprocessing, feature extraction using FFT, and classification of emotions by non-linear classifiers. Section III illustrates the overview of the results and discussion of this present work, and conclusions are given in Section IV.

II. Materials And Experimental Design

A. EEG Data Acquisition

A good database is highly essential for developing intelligent emotion recognition system. There is no universal database is existing for this work. Hence, we designed a customized data acquisition protocol using audio-visual stimuli (video clips) to induce five discrete emotions [7]. All the video clips are collected from various sources such as internet, international standard database, etc. Before showing the stimuli to the experimental subjects, a pilot panel study is conducted over 25 university students to select the most dominant emotional stimuli for evoking unique emotion on the subjects during the data collection. As a result of this pilot panel study, five (5) video clips for three emotions (happy, disgust, surprise) and four (4) video clips have been selected for two (2) emotions from the entire 115 clips of 5 emotions.

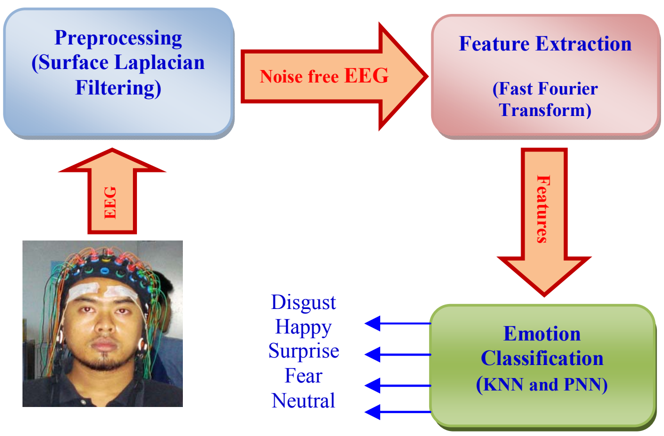

Fig. 1. Emotion Recognition system overview

The selection of video clips is based on self assessment questionnaires mentioned in [8]. The flow of research methodology of this work is given in Figure 2.

The subjects who have undergone for this panel study does not take part in the data collection experiment. The audio-visual stimulus protocol for Trial 1 of our experiment is shown in Figure. 3. From Trial 2 to Trial 5, the orders of the emotional video clips are changed in a random manner. X1 to X5 denote time periods of selected video clips. The time duration of video clips vary from one another.

Three females and seventeen males in the age group of 21~39 years were employed as subjects in our experiment. Once the consent forms were filled-up, the subjects were given a simple introduction about the research work and stages of experiment. The recording of EEG signal has been done through Nervus EEG, USA with 64 channels at a sampling frequency of 256 Hz and band-pass filtered between 0.05 Hz and 70 Hz. Totally, 62 active electrodes, one each for reference (AFz) and ground (Oz) are used in this work. All the electrodes are placed over the entire scalp using International standard 10-10 system. The impedance of the electrodes is kept below 5 kΩ.

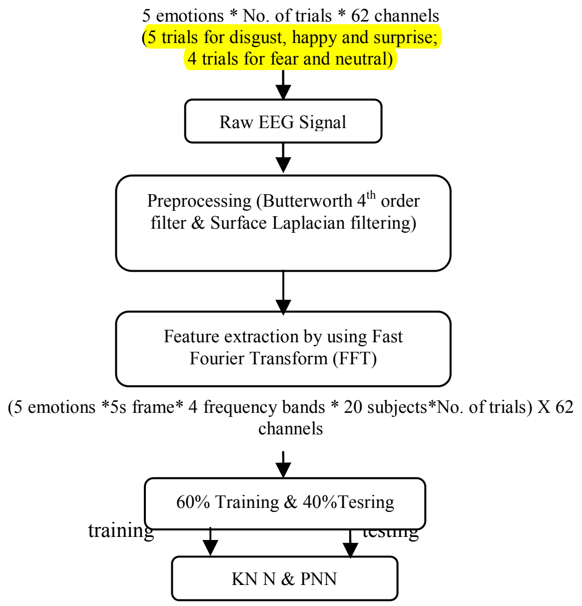

Fig. 2. Experimental flow of emotion recognition using short time EEG signals

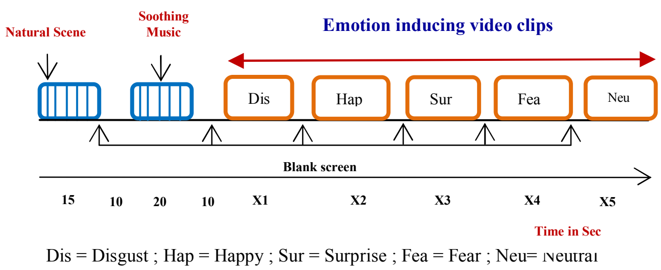

Fig. 3. EEG data acquisition protocol using audio-visual stimulus

Between each emotional video clips, under self assessment section, the subjects were informed to answer the emotions they have experienced [8]. Finally, 5 trials for disgust, happy and surprise emotions and 4 trials for fear and neutral emotions are considered for further analysis.

B. Preprocessing

EEG signals recorded over various positions on the scalp are usually contaminated with noises (due to power line and external interferences) and artifacts (Ocular (Electroocculogram), Muscular (Electromyogram), Vascular (Electrocardiogram) and Gloss kinetic artifacts). The complete removal of artifacts will also remove some of the useful information of EEG signals. This is one of the reasons why considerable experience is required to interpret EEGs clinically [9, 10]. A couple of methods are available in the literature to avoid artifacts in EEG recordings. However, removing artifacts entirely is impossible in the existing data acquisition process.

In this work, 4^{th} order Butterworth filter is used with a cutoff frequency of 0.05 Hz - 60 Hz for removing the noises and artifacts and filtered signals are smoothened using Surface Laplacian (SL) filter. The SL filter is used to emphasize the electric activities that are spatially close to a recording electrode, filtering out those that might have an origin outside the skull. In addition, it also attenuates the EEG activity which is common to all the involved channels in order to improve the spatial resolution of the recorded signal. The neural activities generated by the brain, however, contain various spatial frequencies. Potentially useful information from the middle frequencies may be filtered out by the analytical Laplacian filters. Hence, the signal "pattern" derived from SL filters is similar to "spatial distribution of source in the head".

The mathematical modeling of Surface Laplacian filter is given as:

$$X_{new}(t) = X(t) - \frac{1}{N}\sum_{i=1}^{N} X_i(t) \qquad (1)$$

where X_{new} : filtered signal ; X(t) : raw signal ; N: number of neighbor electrodes

C. Feature Extraction

Extracting the more prominent statistical features from EEG signal is highly inevitable for efficiently classifying the emotions. In general, EEG signal is highly complex and non-linear in nature. However, some of the simple statistical features such as spectral entropy and spectral centroid can give more efficient information about the finer emotional state changes in EEG signals. In this work, the preprocessed EEG signals are framed into 5s frame duration with 50% overlap. Fast Fourier Transform (FFT) is used to extract the above said statistical features from four different frequency bands (alpha, beta, gamma and alpha to gamma) (Eqn 2) [11-13]. Since, the delta and theta are very low frequency range and do not have sufficient information about the emotional state changes during wakeful states. Hence, these two bands are not considered in this analysis. In order to extract the four different frequency bands in EEG signals, this work is proposed to adopt a Butterworth 4^{th} order filter with a different cut off frequency to extract the four frequency bands.

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i2\pi k\frac{n}{N}} \quad k = 0,1,2,.....N-1 \qquad (2)$$

where X_k is the FFT coefficients, N is the total number of input EEG samples, n is total number of points in FFT.

Spectral Entropy (SE) is one of the most significant feature that characterize the EEG signals to easily discriminate the discrete emotions (Eqn 3). This feature reflects the amount of non-linearity presence in the EEG signal. This prominent discrimination property of this feature give rise to use it as a feature in EEG signal processing applications. The variation in amount of non-linearity in EEG signals over different emotional state can be used for emotion recognition.

$$H(x) = \sum_{x \subset X} x_i . \log_2 x_i \qquad (3)$$

Spectral Centroid (SC) is one of the efficient feature in sound (music) recognition. This measure is obtained by evaluating the "center of gravity" using the Fourier transform's frequency and magnitude information. The individual centroid of a spectral frame is defined as the average frequency weighted by amplitudes, divided by the sum of the amplitudes (Eqn 4),

$$Spectral\ Centroid = \frac{\sum_{k=1}^{N} kF[K]}{\sum_{k=1}^{N} F[K]} \qquad (4)$$

where, $F[k]$ is the amplitude corresponding to bin k in FFT spectrum.

D. Emotion Classification

In this work, two simple linear classifiers such as Probabilistic Neural Network (PNN) and K Nearest Neighbor (KNN) are used for classifying the discrete emotions.

A) K Nearest Neighbor (KNN): Among these two classifiers, KNN provides extremely fast evaluations of unknown inputs performed by distance calculations between a new sample and mean of training data samples in each class weighed by their covariance matrices. In addition, KNN is also a simple and intuitive method of classifier used by many researchers typically for classifying the signals and images [20]. This classifier makes a decision on comparing a new labeled sample (testing data) with the baseline data (training data). In general, for a given unlabeled time series X, the KNN rule finds the K "closest" (neighborhood) labeled time series in the training data set and assigns X to the class that appears most frequently in the neighborhood of k time series [22]. There are two main schemes or decision rules in KNN algorithm, that is, similarity voting scheme and majority voting scheme [15].

In this work, the majority voting is used for classifying the unlabeled data. It means that, a class (category) gets one vote, for each instance, of that class in a set of K neighborhood samples. Then, the new data sample is classified to the class with the highest amount of votes. This majority voting is more commonly used because it is less sensitive to outliers. In this experiment, different "K" values ranging from 2 to 10 are tried for determining the emotion classification rate. This value of "K" which gives a maximum classification performance among the other values of K is considered for emotion classification.

B) Probabilistic Neural Network (PNN): PNN is a radial basis network function (RBF) and mainly used in pattern recognition applications. Specht is the person who firstly proposed the PNN [16]. PNN has been widely used for emotion and EEG signal classification in [18-21].]PNN is the implementation of a statistical algorithm called kernel descriminant analysis in which the operations are organized into a multilayered feed forward network.

$$\phi_{ij}(x) = \frac{1}{(2\pi)^{(d/2)}\sigma^d} \exp\left[-\frac{(x-x_{ij})^T (x-x_{ij})}{2\sigma^2} \right] \quad (5)$$

where, d denotes the dimension of the pattern vector x, σ is the smoothing parameter, and x_{ij} is the neuron vector.

PNN is usually performs categorical based target variable classification [16, 17]. It is a feed forward neural network with one input layer, two middle layers called radial basis and competitive layers and the output layer. The input layer unit does not perform any computation and simply distributes the input to the neurons in the pattern layer. On receiving a pattern x from the input layer, the neuron x_{ij} of the pattern layer computes the output.

III. EXPERIMENTAL RESULTS AND DISCUSSION

Among all twenty subjects, 5 trials of three emotions (happy, surprise and disgust) and 4 trails on two emotions (fear and neutral) are preprocessed and sampled for emotion classification. As a total, there are 460 EEG epochs from five discrete emotions. In addition, each epoch is framed into 5s duration to increase the feature vector size for efficient emotion recognition and overlapping of frames with 50%. The number of data points in each epoch depends on the time duration of video clips. In our experiment; the time duration of video clips vary from one another. In this work, a specific interest is shown on selecting the most dominant emotional provoking video clips through pilot panel study and thus confirms the originality of this EEG database. FFT is the most conventional tool used for several applications based on EEG signals. The proposed digital filters perform well on noises and artifact removal. The two most dominant type of frequency domain features such as spectral entropy and spectral centroid is derived from the EEG signals for emotion classification. The entire feature vector is divided into 60% for training the classifier and 40% for testing the syste~~m~~. The next stage is to train the KNN and PNN classifier with a best value of K and P, respectively on classifying the emotions. The classification ability of a statistical feature set can be measured through classification accuracy by averaging five times. The value P value in PNN is changed from 0.1 to 0.9. The best value of P is chosen based on the higher mean emotion classification rate.

From Table 1, the lower value of K give the best mean emotion classification rate compared to PNN. The maximum mean emotion classification rate of 91.33% is achieved on both KNN and PNN classifiers in Spectral Entropy features derived from Beta band. In contrast, Spectral Centroid feature gives the maximum mean emotion classification rate of 84% in KNN and 83.64% in PNN. This highest emotion recognition rate is only possible due to the short time analysis on EEG signals. Since, emotion is a transient phenomenon and occurs and retain for a smaller time duration in the subject's mind. In the case of analyzing the entire video clips duration on EEG signals, most of the instant is become more silent and does not contain any information about the emotional state changes. Also, the underlying brain activity over neutral state of the subjects and other mental thinking will severely contaminates the EEG signals.

In terms of frequency bands, beta frequency band has more useful information about emotional perceptions of the subject's over other frequency bands. Though alpha band is more responsible for wakeful state but it does not play any role on this present analysis to determine the emotions of the subjects. Compared to the statistical feature, spectral entropy give more efficient information about the emotion recognition in contrast with spectral centroid. This feature is not much significant on this present study to enhance the potential of emotion recognition rate. In PNN and KNN classifier, the lower value of P and K, respectively gives the maximum mean emotion classification rate. In real time scenario, the higher value of P is more prominent for good discrimination between the classes. In future, this work aims to investigate the reduced feature set through Principal Component Analysis (PCA) on studying the performance of emotion classification. In addition, further research investigations can be done through the time duration of the EEG signals >5s to see their response on finding the emotional state changes. Simple non-linear classifier (KNN) giving the maximum mean emotion classification rate compared to other classifiers and also with earlier works. Thus, the proposed methodology is highly efficient to tract the finer changes in emotional states through EEG signals. All the programming was done in MALAB environment on a desktop computer with Intel I3 processor 2 GHz speed with 2 GB of random access memory.

TABLE I. KNN BASED CLASSIFICATION OF EMOTIONS USING FFT OVER DIFFERENT FREQUENCY BANDS

K Value	Alpha		Beta		Gamma		All Freq Bands	
	SE	SC	SE	SC	SE	SC	SE	SC
2	82.5833	62.09	91.3333	68.96	91.1667	78.96	90.6667	84.00
3	74.9167	58.00	83.25	65.30	83.5833	74.87	83.4167	81.08
4	71.25	55.59	78.1667	63.04	78.75	73.48	76.4167	80.20
5	68.1667	53.76	74.5	61.36	73.25	72.39	72.1667	77.50
6	66.8333	52.01	72.4167	59.82	70.3333	71.59	71.8333	76.99
7	64.3333	51.35	69.0833	58.88	67.8333	69.39	68.9167	74.80
8	63.5	51.21	67.9167	57.71	65.25	69.32	67.5833	72.90
9	62.1667	49.82	65.8333	56.98	64.3333	67.79	65.4167	71.51
10	61.0833	48.36	64.5833	56.76	62.6667	66.47	63.8333	71.07
Minimum	**61.0833**	**48.36**	**64.58**	**56.76**	**62.6667**	**66.47**	**63.8333**	**71.07**
Maximum	**82.5833**	**62.09**	**91.33**	**68.96**	**91.1667**	**78.96**	**90.6667**	**84.00**
SC: Spectral Centroid; SE: Spectral Entropy								

TABLE II. PNN BASED EMOTION CLASSIFICATION USING FFT OVER DIFFERENT FREQUENCY BANDS

P Value	Alpha		Beta		Gamma		All Freq Bands	
	SE	SC	SE	SC	SE	SC	SE	SC
0.1	82.17	61.43	91.33	68.88	91.33	78.89	90.58	83.64
0.2	79.17	58.36	90.5	69.17	91.25	77.87	90.75	83.20
0.3	59.25	50.91	86.58	58.14	90.17	71.73	89.58	80.28
0.4	53.42	42.44	63	50.84	78.33	57.41	86.5	67.57
0.5	41.67	38.71	54.17	48.72	55.92	51.28	65.5	55.73
0.6	39.17	38.35	51.5	44.70	53.17	49.01	55.17	52.52
0.7	39.17	38.35	41.92	39.37	48.25	45.95	53.17	50.11
0.8	39.17	38.35	40.67	38.35	39.83	40.98	47.33	47.63
0.9	39.17	38.35	40.67	37.76	38.75	38.86	40.17	45.14
Minimum	39.17	38.35	**40.67**	37.76	38.75	38.86	40.17	**45.14**
Maximum	82.1667	61.43	**91.33**	69.17	91.33	78.89	90.75	**83.64**
SC: Spectral Centroid; SE: Spectral Entropy								

IV. CONCLUSION

This present work is aim to analyze the short time EEG signals for emotion classification using Fast Fourier Transform (FFT). The proposed two statistical features performs better on classifying the emotions using two simple classifiers (KNN and PNN). However, KNN performs well over PNN with lesser computational complexity and giving the maximum mean emotion classification rate of 91.33% on classifying five emotions. In this work, we also analyzed the EEG signals over different frequency bands for emotion classification. Beta frequency band give more finer information's about the emotional state changes of the subjects over other frequency bands. In addition, these results also confirm our hypothesis that it is possible to differentiate and classify the human emotions the linear and non-linear features. The results of this study provide a framework of methodology that can be used to elucidate the dynamical mechanism of human emotional changes underlying the brain structure. In addition, the results can be extended to the development of online emotion recognition system.

REFERENCES

[1] Bung H, and Furui S, "Automatic Recognition and understanding of spoken languages- a first step toward natural human machine communication", *Proceedings of IEEE*, vol. 88, issue. 8, pp, 1142-1165, 2000.
[2] Cowie R, Douglas E, Tsapatsoulis N, Votsis G, Kollias G, Fellenz W and Taylor J G, "Emotion Recognition in human-computer interaction", *IEEE Signal Processing Magazine*, pp, 3773-3776, 2001.
[3] Kim K.H, Band S.W, and Kim S.B, "Emotion Recognition System using short-term monitoring of physiological signals", *Proceedings on Medical & Biological Engineering & Computing*, vol. 42, pp, 419-427, 2004.

[4] Chanel G., Karim A.A. and Pun T, "Valence-arousal evaluation using physiological signals in an emotion recall paradigm", *Lecturer Notes in Computer Science*, Springer, pp, 530 – 537, 2007.

[5] Kazuhiko T, "Remarks on emotion recognition from bio-potential signals", *2nd International Conference on Autonomous Robots and Agents*, New Zealand, pp, 186–191, 2004.

[6] Murugappan M, Rizon M, Nagarajan R and Yaacob S, "Inferring of Human Emotion States using Multichannel EEG", International Journal of Soft Computing and Applications (IJSCA), EURO Journals, vol.48, no.2, pp.281-299, 2010.

[7] Murugappan M, Rizon M, Nagarajan R and Yaacob S, "An Investigation on visual and audiovisual stimulus based emotion recognition using EEG", *International Journal on Medical Engineering and Informatics*, vol. 1, no 3, pp, 342-356, 2009.

[8] Murugappan M, Rizon M, Nagarajan R and Yaacob S, Hazry D, and Zunaidi I, "Time-Frequency Analysis of EEG Signals for Human Emotion Detection", *IFMBE Proceedings*, no. 21, pp, 262-265, 2008, Springer Book chapter.

[9] Jung T, "Removing Electroencephalographic Artifacts by Blind Source Separation", *Journal of Psychophysiology*, vol. 37, no. 2, pp, 163-178, 2000.

[10] Gott P. S, Hughes E. C, and Whipple, "Voluntary Control of Two Lateralized Conscious States: Validation by Electrical and Behavioral Studies", *Journal of Neuropsychological*, vol. 22, pp, 65-72, 1984.

[11] Mallat S. G, "A Theory for Multi-Resolution Signal Decomposition: The Wavelet Representation", *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, no 7, pp, 674–693, 1989.

[12] Merzagora A.C, Bunce S, Izzetoglu M., and Onaral B "Wavelet Analysis for EEG Feature Extraction in Deceptive Detection". *IEEE Proceedings on Engineering in Medicine and Biology Society,* pp, 2434-2437, 2006.

[13] Chethan P and Cox M, "Frequency Characteristics of Wavelets", *IEEE Transactions on Power Delivery*, vol. 17, no. 3, pp, 800-804, 2002.

[14] Charles W.A. and Zlatko S, "Classification of EEG signals from four subjects during five mental tasks", *IEEE Proceedings on Engineering Application in Neural Networks*, pp.407–414, 1997.

[15] Wanpracha A C, Ya-ju Fan, and Rajesh C S, "On the Time Series K-Nearest Neighbor Classification of Abnormal Brain Activity", *IEEE Transactions on Systems, Man and Cybernetics – Part A:Systems and Humans* , vol. 37, no. 6, pp, 1005-1016, 2007.

[16] Jia H, "Classification of EEG signals of Different Mental Tasks Based on PNN Neural Network", *International Proceedings of Computer Science and Information Technology,* vol 43, pp. 2-6, 2012.

[17] Murugavel ASM, Ramakrishnan S, Balasamy K, Gopalakrishnan T, "Lyapunov Features Based EEG Signal Classification by Multi-Class SVM", Proceedings on World Congress on Information and Communication Technologies, pp, 197-201, 2011.

[18] Saadat N and Hossein P, "An Optimal EEG - based Emotion Recognition Algorithm using Gobor Features", WSEAS Transactions on Signal Processing, vol 3, issue 8, pp, 87-99, 2012.

[19] Mehrnaz K H and Abbas E, "An Online EEG-based brain computer interface for controlling hand grasp using an adaptive probabilistic neural network", Medical Engineering and Physics, 2010, doi:10.1016/j.medengphy.2010.04.016

[20] Chi-Keng W, Pau-Choo C, and Chi-Jen W, ""Representative Segment - Based Emotion Analysis and Classification with Automatic Respiration Signal Segmentation", IEEE Transactions on Affective Computing, vol 3, no 4, pp, 482-495, 2012.

[21] Shweta K, "Classification and Clustering of Brain Seizure Activity using Wavelet Transform and Radial Basis Neural Network", International Journal of Scientific and Engineering Research, vol 3, issue 12, pp, 1-6, 2012.

[22] Xiao- Wei W, Dan N and Bao-Liang L, "EEG-Based Emotion Recognition using Frequency Domain Features and Support Vector Machines", *Lecture Notes on Computer Science,* vol 7062, pp, 734-743, 2011.