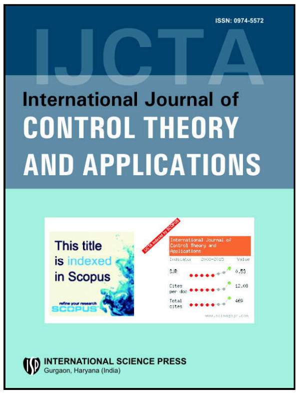

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A Comparative Study of Existing EEG based Emotion Recognition Techniques

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Abstract: An emotional state of user has garnered increasing attention over the last few years in the research areas of Human Computer Interaction (HCI) and Brain Computer Interface (BCI). Emotions include cognitive as well as perspective process. Various modalities contribute to recognize human emotions using machine, out of which EEG is one of the prominent and convenient modality to recognize human emotions. This paper provides comprehensive review of existing EEG based emotion recognition techniques along with some insights related to challenges in future research and development issues. It also includes comparison based on different proposed parameters for EEG based emotion recognition.

Keywords: Electroencephalogram (EEG), Human Computer Interaction (HCI), Brain Computer Interface (BCI).

I. INTRODUCTION

An emotional state of user has garnered increasing attention over the last few years in the research areas of Human Computer Interaction (HCI) and Brain Computer Interface (BCI). Emotions include cognitive as well as perspective process. Basic and dimensional model represents and classify the emotions. Basic model composed of eight basic emotions such as *anger, fear, happiness, surprise, disgust, curiosity and acceptance* [1][2]. Dimensional model uses emotion scale with respect to arousal and valence as shown in Fig.1. Arousal is more general property of stimulus which refers to level of activation indicating the degree of excitement i.e. calm to excite whereas valence indicates positive and negative emotions [3]. To standardize the experimental framework for research in human emotions against the two dimension scale, the International Affective Picture System (IAPS) database and International Affective Digitized Sound databases (IADS) are used which include pictures and sounds labeled with valence and arousal values [4][5]. In order to recognize the human emotion by computer or machine various approaches exist such as facial expressions, speech and gestures. The signals captured from Autonomous Nervous System (ANS) are also contribute to human emotion recognition approaches [6]. Moreover, it is accepted that Central Nervous System (CNS) usage is beneficial for emotion recognition over above mentioned emotions recognition approaches. In CNS, signals are captured from origin of the emotion genesis i.e. from brain signals which are captured with the help of Electroencephalogram (EEG), Positron Emission Tomography (PET), Magnetoencephalogram (MEG) and functional Magnetic

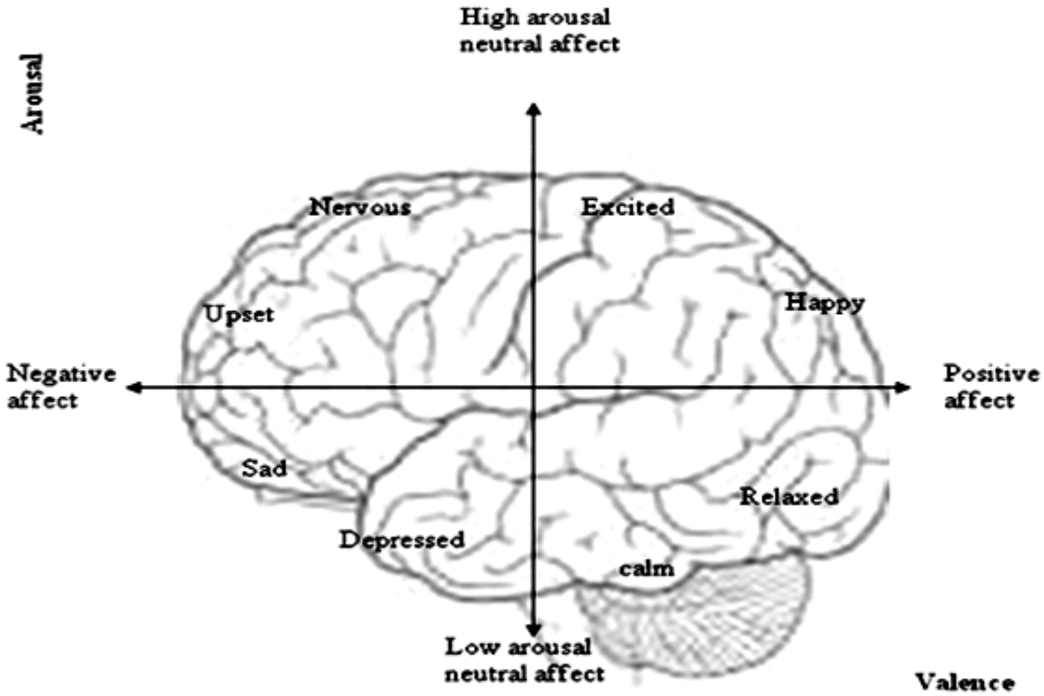

Figure 1: Two Dimensional Model of Emotion on Arousal and Valence Scale

Resonance Imaging (fMRI). EEG appears to be less intrusive and one of the best time suiting than other three aforementioned [7][8].

This paper will focus on the following issues related to EEG based emotion recognition techniques. First, we start with quick review of related work which includes way of emotion elicitation, feature extraction and classification methods. Then we show the comparison of EEG based emotion recognition techniques based on some proposed parameter. Lastly, we discuss some challenges and future directions for EEG based emotion estimation.

2. RELATED WORK

EEG based emotion recognition consists of three steps namely; emotion elicitation, captured data preprocessing, and classification. Emotion elicitation includes generating artificial emotions to the participants using pictures, movies, sounds with predefined emotional reference. In captured data preprocessing frequency band selection and noise removal is performed for recorded signals. The classification involves feature extraction techniques and classification methods to classify the recorded signals in different groups of emotions [9]. Discarding the useless non-emotional information from the captured dataset has become an important part of EEG based emotion recognition. The first attempt towards such direction is introducing novel index namely; asymmetry index (AsI) and utilizing multidimensional directed information (MDI). It is noticed that, EEG signals which refer to distinct emotion elicitation trials with big AsI values are more effective for discriminating emotions in classification step [10]. Also, a two step classification procedure exists for discrimination of emotional state evoked by pleasant and unpleasant stimuli that varies in arousal levels. Mahalanobis Distance (MD) based classifier and Support Vector Machines (SVM) methods are applied for classification and preprocessing of data is performed using EEGLAB tool. The result shows the robust classification procedure for classification of emotions [11][12]. For dealing with asymmetric behavior of emotions and analyzing them in two dimensions, emotions are organized around approach withdrawal tendencies and differentially lateralized in frontal region of brain. The left frontal area of brain is involved in experience of positive emotions such as happiness whereas the right frontal region is involved in experience of negative emotions such as fear or disgust. The attempt has been made to differentiate the emotions of happiness and disgust with EEG signals captured from left and right frontal, central, anterior, temporal and partial regions of the brain. F3, F4, C3, C4, T3, T4 and P3, P4 regions are used with the help of electro-Cap according to 10-20 system. The results revealed that the power of alpha band (8-12 Hz) of EEG signal is concerned with disgust condition for both frontal and anterior temporal region [13][14]. Based neuroscience literature of the heterogeneity of different sectors of prefrontal cortex (PFC), asymmetry concept is applied to PFC. The role of PFC in affective expression has been predicted and found that along with alpha,theta (4-7 Hz), beta (13-30 Hz), and gamma (31-100 Hz) bands also contribute in generating the emotions [15].

Emotion recognition based on EEG signals involves feature extraction and classification of EEG signals for distinct emotional states. Six statistical features are examined using EEG data including mean of raw signals, standard deviation of raw signals, mean of absolute value of first differences of raw and normalized signals, and mean of absolute value of second differences of raw and normalized signals for feature extraction and artificial neural network for classification. The statistical features have been fed individually as well as the combinations of the features have been developed and fed to the neural network. The highest classification rate is achieved by combining the mean of first differences of raw signals with mean of absolute value of second differences of raw signals [16]. Further, the same six statistical features are classified using back propagation neural network. Input extracted from combination of various sets of emotions has been used to train and test this neural network. The result revels that the performance of neural network has been affected by number of categories to be classified, by reducing the number of states to classify, improving the performance of classification. Consequently, the comparison has been made based on the correct classification as well as time consumed for training the neural network [17]. Fuzzy-C-Means (FCM) and Fuzzy-K-Means (FKM) clustering methods improve the performance of classification; the features are extracted using the Doubenchies order 4 wavelet transform (db4). It has been noticed that FKM clustering performs well for clustering the emotional data of 24 channels than 63 channels of EEG data while FCM based clustering perform well for both 24 and 63 channels of EEG data [18]. Further, the combination of Surface Laplacian (SL) filtering, time frequency analysis of wavelet transform (WT), and linear classifiers classify the discrete emotions. The SL filtering method has been applied for noise removal from the raw EEG signals. Due to optimal time frequency localization properties of wavelet functions, the db8, *sym8* and *coif5* decompose the EEG signals into five different EEG filtering bands (delta, theta, alpha, beta and gamma). Further, in order to evaluate the efficiency of emotion classification under different sets of EEG channels, the classification accuracy of original sets of channels is compared with reduced set of channels (62 channels vs. 24 channels). For classification, Linear Discriminant Analysis (LDA), and K- Nearest Neighbor (KNN) are used and found that KNN works better for 62 as well as 24 channels [19].

Next, Higher Order Crossings (HOC) approach for feature extraction scheme with HOC-emotion classifier (HOC-EC) for robust classification is tested against four different classifiers namely; Quadratic Discriminant Analysis (QDA), KNN, MD, and SVM. It is found to be more robust and consistent for effectively discriminating the emotions from EEG signals [9]. In addition, a user independent emotion recognition system termed as Hybrid Adaptive Filtering and Higher Order Crossings (HAF-HOC) uses genetic algorithms for decomposing the EEG signals to the empirical mode. For data acquisition a series of facial expressions, image projection as a Mirror Neuron System (MNS), and EEG signals using three channels have been used. The system shows that HAF-HOC provides the higher classification rate [8]. A novel emotion elicitation approach provides a novel method for evaluating the emotion elicitation procedures in EEG setup. It employs the frontal brain asymmetry theory including an asymmetry index (AsI). This approach is based on three channels EEG recordings and the classification process is conducted using higher-order crossings and cross correlation (HOC-CC) and, SVM classifiers, showing an efficient evaluation criterion for emotion elicitation process. However, it suffers from the reliability to larger data set and lager scale experiments [22]. EEG signal segmentation in time frequency domain for effectively retrieving the emotion related information within the EEG recordings uses feature vector construction set, constructed using HOC-CC and classification using SVM. The signal segments with less emotional information are discarded and keeping only the valuable ones. Thus, it contributes to a more reliable EEG based Emotion Recognition [23].

A six-layer biologically inspired feed forward neural network discriminates the emotions from EEG signals on two dimensional scale. The network is comprised of shift register memory, spatial filtering for input layer and the estimation of coherence between each pair of input signal for hidden layer. The accuracy of neural network is compared with various feature extraction methods and classified using different feed forward learning algorithms such as Naïve Bayesian, Extreme Learning Machine and General Regression Neural Network. This network provides highest accuracy when used with radial basis function [24]. Subsequently, an adaptive approach human affect detection from EEG classification, and finding the optimal combination of classifiers and feature sets to deliver the optimal performance for emotion recognition presents the performance comparison of KNN, SVM and Naïve Bays using adaptive classification technique. An adaptive version of algorithm is evaluated, showing the error rate for static version of each algorithm is higher than the adaptive version [28].

3. COMPARISON BASED ON DIFFERENT PARAMETERS

We have attempted to compare EEG based emotion recognition techniques described in literature on the basis of the some proposed parameters. Table 1 depicts the comparison based on above mentioned parameters. Feature extraction method indicates method used to extract the appropriate features from recorded EEG data related to emotions. Classification method indicates classifier used for discriminating different emotions, number of channels or electrodes of EEG recording device, frequency bands used for analyzing particular emotion, location of electrodes on brain. Time constraint specifies whether it is real time emotion recognition or not. All whole emotion recognition process is classified as good or better based on its percentage accuracy.

4. CONCLUSION

This field of research has received a great deal of attention because it can help to analyze the human emotion not only from the external part of the body of human being but also its internal feelings. It will help to recognize the real feeling and not the posed emotions. This study provides the review of available ways to recognize the emotions from brain waves captured in the form of EEG signals. EEG signals are associated with alpha (8-12

Table 1
Comparison of Existing EEEG based techniques with respect to different parameters.

Sr. No.	*Feature Extraction Method*	*Classification Method*	*Number of Channels*	*Frequency Bands*	*Recognized Emotions*	*Location*	*Time Constraints*	*Accuracy*
1	SVM [25]	Neural Network	3	Delta, theta, alpha and beta	Joy, anger, fear and relax	-	Offline	41.7%
2	HOC and CC [23]	Quadratic Discriminant Analysis, Mahalanobis, KNN and SVM	3	Alpha and beta	Arousal and valence	Fp1, Fp2, F3 and F4 (F3 and F4 as dipole)	Offline	64.17% to 82.91%
3	HOC and CC (asymmetry index) [22]	SVM	3	Alpha and beta	Arousal and valence (LALV, LAHV, HAHV, HALV)	Fp1, Fp2, F3 and F4 (F3 and F4 as dipole)	Offline	62.58% for user independent 94.40 for user dependant
4	HOC [8]	QDA, MD,	3	Alpha	Happy,	Fp1, Fp2,	Offline	62.3%

(*contd...Table 1*)

Sr. No.	*Feature Extraction Method*	*Classification Method*	*Number of Channels*	*Frequency Bands*	*Recognized Emotions*	*Location*	*Time Constraints*	*Accuracy*
		k-NN where k=3 and SVM		and beta	sad, fear, disgust, surprise, anger	F3 and F4 (F3 and F4 as dipole)		for QDA 83.33% for SVM
5	HOC and HAF [9]	QDA, MD, k-NN and SVM	3	Alpha and beta	Happy, sad, fear, disgust, surprise, anger	Fp1, Fp2, F3 and F4 (F3 and F4 as dipole)	Offline	85.17%
6	Discrete Wavelet Transform (db4) [18]	Fuzzy-C-Means and Fuzzy-K-Means	63 and 24	Alpha	Happy, fear, disgust	62 electrodes + AFz and Oz	Offline	Reduced the number of channel from 64 to 24
7	Three wavelet functions “db8”, “sym8” and “coif5” [19]	Combination of spatial filtering, wavelet transform and linear classifier (KNN and LDA)	64 channels and 24 channels	Delta, theta, alpha, beta, and gamma	Disgust, happy, surprise, fear, anger, neutral	62 electrodes + AFz and Oz	Offline	83.04 on 64 channels and 79.17 on 24 channels (KNN)
8	Six statistical features as mean, standard deviation and means and absolute values of first differences of raw signals, means and absolute values of second differences of raw signals and normalized signals [16]	Artificial Neural Network	64 channels	-	Anger, sad, happy, and neutral	All 64 channels	Offline	90%
9	Two layer radial basis function [24]	ERNN (feed forward neural network)	8	Theta, alpha, beta, gamma	Arousal and Valence	F3, F4, C3, C4, T7,T8, P3, P4	Offline	65.85% for arousal 67.3% for valence
10	ERP [12]	MD and SVM	3	Delta, theta, alpha	Happy, sad, fear, disgust, surprise, anger	Fz, Cz, and Pz	Offline	79.5% and 81.3%

Hz), beta (13-30 Hz), theta (4-7 Hz) and gamma (31-100Hz) frequency bands. From these bands decreased power in alpha band was found to be associated with emotional state. Above all this, one may find the characteristics of all remaining bands for emotion detection. The comparison of feature extraction and classification methods by different researchers shows that the statistical features for feature extraction and design of some kind of neural network gives higher accuracy, however it may depend on the procedure of recording the EEG data, emotion elicitation process and the dataset size.

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