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Comparison of ERP & Entropy based Emotion Classification using EEG signals

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Abstract: Emotions are necessary to understand the behavior of an individual. It is elementary to human understanding andrealistic decision-making. Since number of techniques can be used for emotion recognition such as voice, facial expression of an individual but these channels can be faked. In this paper, main emphasis is given toward the acquisition of EEG signal by emotion evoking picturesprovided by International Affective Picture System (IAPS) from three subjects. The EEG signal is decomposed 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 from these five frequency bands has been extracted.The ERP potentials such as P100, N100 and the two latencies corresponding to these bio potentials also extracted for every class of emotion from preprocessed EEG signals. The training and testing is performed on both the attributes extracted from EEG signal for classification of emotions into two classes. The classification is performed using LIBSVM (RBF kernel)with 3 fold cross validation to classify the emotions along arousal axis. It has been found that the accuracy obtainedisconsistently high for Event related potential as compared to Entropy attribute. The maximum accuracy of 79.16% has been achieved along ERP attribute and 68.5% along Entropy attribute.
Keywords: Entropy, Event related potential (ERP), Classification.

1. Introduction

Emotions can be defined as mental and physiological state of human related with a wide variety of feelings, thoughts, and behavior [1].Emotions are temporary feeling that comes from a particular cause [2].It includes different experience such as trust, hate, anger, joy and fear of human being which can predict the personality of an individual.The emotion model was given by many researchers like Darwin, Plutchik and Ekman. The first model was given by Darwin followed by Plutchik and Ekman. Plutchikconsidered that there are eight basic emotions such as surprise, sadness, disgust, acceptance, joy, anger, fear, joy, and curiosity [3].While Ekman considered that all emotions are made up of six basic feelings namely happiness, sadness, anger, fear, disgust and surprise [4].Emotions not only affect our actions but also the way we communicate with the surrounding.Mostly computers are unable to understand the needs of human being to respond automatically so it is not possible to correctly identify the all emotional states of human to take the appropriate actions upon processing on collected data [5]. So emotion recognition is very important aspect to understand the behavior of human. It can helps in reducing the communication hindrance with the environment. For example, a person driving on road in bad mood is not only harmful to himself but also to other natives on the same road. So this requires developing a methodology to bring the subject from aroused state of mind to relaxed state of mind.The emotions can be predicted from face, voice or gestures of human but studying emotions through EEG signal is simple method because it involves a portable hardware and direct measurement of electrical activity [6]. The recognition of emotion become possible when represented in a three dimensional plane. Russell, J.A (1980) provide a circumflex model of affect in which emotions were described in a two dimensional plane. According to approach, pleased was along x axis and unpleased was along y axis [7]. Later this model was improved by Lang et al where valence and arousal was representing along two dimensions [8].
Some of the basic emotions as described in Figure 1.

Figure 1: Basic Emotions

2. Review

Picard, R.W *et al.* (2001) in their research study worked on eight classes of emotions such as grief, love, hate, romantic love, nature, joy including neutral. The guidelines laid down by Clynes were used for evoking the emotions [9]. The data was collected from single participant with the help of four sensors such as Photoplethysmyograph, skin conductance sensor, Electromyogram, Hall Effect respiration sensor for classification of eight emotional states. The attributes extracted was statistical such as mean and standard deviation of signals. Through the use of Maximum a Posteriori (MAP) classification technique using Fisher analysis, classification was performed. An accuracy of about 80% to 90% was achieved. Takahashi, K *et al.* (2004) as well used physiological database for classifying emotions into five states namely joy, anger, sadness, happiness and relax from twelve subjects. The classifier used was support vector machines for classification of emotions over setup of three dry electrodes with recognition rate of 41.7% were achieved [10].
Frantzidis, C. A *et al* (2008) collected the EEG data from central nervous system and skin conductance response from 13 male and female subjects. The emotions were invoked by using the images from IAPS dataset [11]. The pictures from IAPS are divided into four categories named as HVHA means pleasant and having high arousal in upper right corner, and similarly upper left corner denoting as HVLA means pleasant but in low arousal stimuli. In the same way LVHA in lower right quadrant representing unpleasant in high arousal stimuli and LVLA in lower left quadrant is unpleasant in low arousal state. The EEG signals were collected from three central electrodes namely Fz, Cz and Pz. The attributes such as event related potential (ERP), latency, rise time, amplitude and the skin resistance response duration were extracted for classification of emotions. The classification was performed using artificial neural network that yielded an accuracy of 80% for joy, 100% for fear, 80% for happiness, and 70% for melancholy [12].The IAPS database 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 were extracted. Support vector machine was used a classifier for classification of emotions in to two classes [13] [14].

Murugappan, M *et al*. (2009) acquired EEG for classification of emotions into five classes such as disgust, happy, surprise, fear and neutral from 20 healthy subjects. The data was acquired by audio-visual stimuli to the subjects. The EEG signal with the help of wavelet transforms, was decomposed into five different frequency bands (delta, theta, alpha, beta and gamma). Linear discriminate analysis (LDA) & K Nearest neighbor (KNN) classifier was used for classification of emotions. An average accuracy of 79.14% was obtained with maximum subset emotion rate of 73.75% on fear, 91% on disgust, 60% on surprise, and 88% on happy, and 87.5 % on neutral emotions was achieved [15].

Singh, M. *et al.* (2013) used the eNTERFACE 06 EEG database for classification of emotions along valence axis [16]. The attributes such as Power Spectral Density (PSD), Short Time Fourier Transform (STFT), event Related Potential (ERP), power, Entropy and variance on the basis of time frequency domain were extracted. Through the classifiers such as ANN and Naïve Bayes, classification of emotions was done into two classes [17-21]. Zheng, W.L*et al.* (2014) classified emotions into two states (positive and negative) when EEG data was collected by stimulating the subject with emotional movie clips from three male and female subject using 62-channel electrode cap placed according to the international 10-20 system. In addition to this new technique was incorporated namely hidden markov model (HMM) to accurately capture a more consistent emotional stage. The attributes extracted for emotion classification was differential entropy features. Through the use of KNN (k-Nearest Neighbor), SVM (support vector machine), GELM (Graph regularized Extreme Learning Machine), DBN (Deep Belief Networks) and DBN-HMM classifier, an average accuracies of 69.66%,84.08%, 85.67%, 86.91% and 87.62% was achieved. Results showed that using the DBN and DBN-HMM models accuracy of EEG based emotion classification was improved in comparison to other methods [22].

3. EEG signal acquisition

This section provides the methodology followed for acquisition of EEG signal. Three subjects, who are male candidate with no history of health diseasehas been used for acquiring the EEG signal. The BIOPAC data acquisition unit MP150 interfaced with EEG cap is used. EEG cap has totaled of 20 electrodes as per international 10-20 system as described in Figure 2.

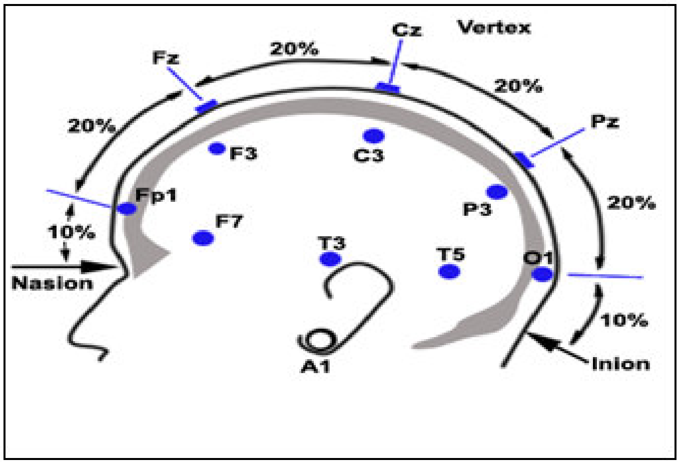

Figure 2: International 10-20 System [23]

By stimulating the subject with emotion evoking images from international affective picture system (IAPS), datais acquired. The images from IAPS were collected at university of Florida by the scientist of mental health centre of emotions (NIMH).Emotion evoking image isshown to subject for 1second followed by plus symbol for 1.5seconds [24].On the basis of perfect synchronization, EEG data is acquired when images on display systemis shown to subject under observation [25]. The acquisition of EEG signal is at sampling rate of 500samples per second.

4. Signal conditioning

After the collection of EEG signal, conditioning of EEG signal is performed. The signal is preprocessed using available ACQ 4.2 softwareprovided by BIOPAC [26]. Preprocessing is performed in offline mode to obtain the better results of classification. The EEG signals are brought in the range of 0.5Hz to 40Hz with a low pass IIR filter having cut off frequency of 40Hz and high pass IIR filter having cut off frequency of 0.5Hz.The comb band stop filter is used to eliminate the power noise having notch frequency of 50Hz.

5. Feature Extraction

The preprocessed EEG signal has been used to extract the features. The extracted attributes are the event related potential and entropy from the EEG data.

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 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 [27]. Another feature extracted from EEG data is event related potential.

The features extracted for emotion classification are P100, N100, PT100 and NT100. P100 is the max peak observed between 80ms to 120ms after the onset of stimuli, so P100 is considered as the maximum ERP of the subject in the time limit of 80 to 120ms. PT100 is the latency corresponding to the time (in ms) at which P100 occurs. N100 is min peak observed between 80ms to 120ms after the onset of stimuli, so N100 is considered as the minimum ERP of the subject in the time limit of 80 to 120ms. Similarly NT100 is the latency corresponding to the time (in ms) at which N100 occurs.

6. Classification

After the extraction of features from preprocessed data, the EEG data has been used for classification of emotions into two classes' namely High Valence High Arousal and High Valence Low Arousal. The classification is performed using LIBSVM classifier (3 fold cross validation)with RBF kernel on two frontal electrodes namely F3 and F4. LIBSVM is software that is being used for support vector classification, distribution estimation and regression. It has various features like efficient multi-class classification, cross-validation for the selection of best model, availability of various inbuilt kernels likepolynomial kernel, linear kernel, RBF kernel etc. [28].

Figure 3shows the basic classification criteria of support vector machine.

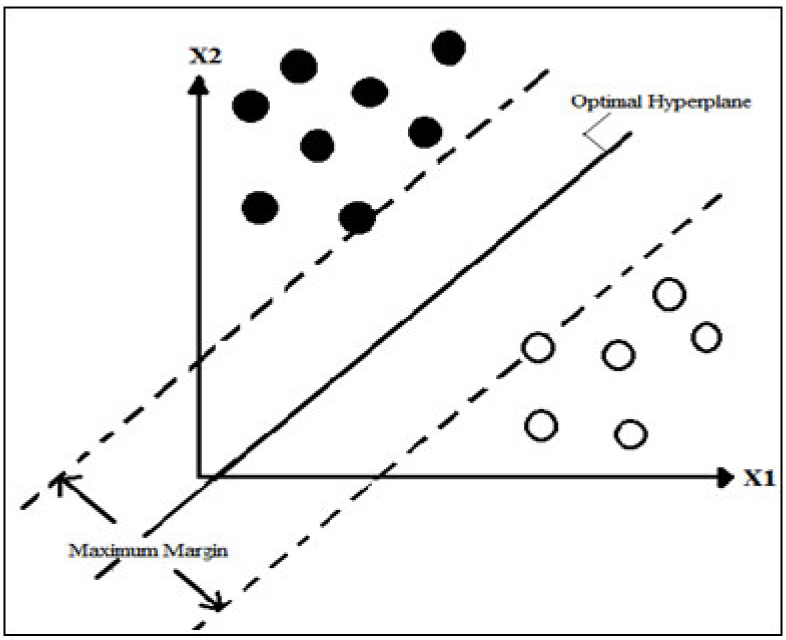

Figure 3: General Support Vector Classification

These classifiers are applied in MATLAB for classifying the signals. Classification accuracy is then calculated accordingly depending upon how many signals are classified correctly.

7. Results& Discussion

The study has been conducted on different attributes namely event related potential and entropy for classification of emotions into two classes. The analysis is performed on frontal electrodes namely F3 and F4 electrode. The training and testing on each subject is performed separately from extracted attributes of EEG signal. It is carried out in such a way that total of 70% samples is used for training and remaining 30% is used for testing. The best model is determined by calculating cost factor and gamma by training the model for every subject. Using this best model, testing is performed on remaining 30% test dataset of every subject. The classification accuracy obtained for ERP as attribute is shown in Table 1.

Table 1: Classification accuracy obtained for attribute Event related potential

Subjects	**Highest Accuracy of electrodes (%)**		
	F3 Electrode	**F4 Electrode**	**Best accuracy**
Subject 1	73.68	68.42	73.68
Subject 2	70.80	79.16	79.16
Subject 3	70.80	75	75

It can be seen that when extracted attribute Event related potential is taken, it has been found that an accuracy of 73.68% is achieved at F3 electrode and 68.42% at F4 electrode for subject 1. In the same way for subject 2, an accuracy of 70.80% has been obtained at F3 electrode and 79.16% at F4 electrode. For subject 3, an accuracy of 70.80% has been obtained at F3 electrode, 75% at F4 electrode. It shows that highest accuracy of 79.16% has been obtained which is consistently high among other subjects. Thus accuracy obtained for all subjects ishighestwhen emotions are classified along arousal axis with ERP attribute.

In the same way,theextracted attribute Entropy by decomposingthe EEG signal into five frequency bands isconsidered for classification of emotions. It has been found out that accuracy obtained iscomparatively lower than ERPat F3 and F4 electrode when individual subject for classification is considered.The classification accuracy obtained for Entropy as attribute is shown in Table 2.

Table2:Classification accuracy obtained for attribute Entropy

Subjects	**Highest Accuracy of electrodes (%)**		
	F3 Electrode	**F4 Electrode**	**Best accuracy**
Subject 1	62.5	58.89	62.5
Subject 2	63.42	66.66	66.66
Subject 3	68.5	66.66	68.5

It shows that highest accuracy of 68.5% has been obtained which is consistently high among other subjects for Entropy attribute

When both the features namely Event related potential and Entropy iscompared for classification of emotions, it can be seen that highest accuracy among all subjectshas been achieved for event related potential attribute. Whereas for extracted attribute Entropy, it can be seen that accuracy obtained is comparatively low among all subjects. The classification accuracy obtained with different attribute is shown in Table 3.

Table3: Comparison of classification accuracy obtained with different features

Features used for classification	**Subject 1**	**Subject 2**	**Subject 3**
Event related potential	73.68	79.16	75
Entropy	62.5	66.66	68.5

It can be seen that the accuracy achieved isfar better for extracted attribute Event related potential than Entropy when emotions are classified into two classes along arousal axis. The best classification accuracy obtained subject wiseoncomparingboth of attributes is shown in Figure 4.

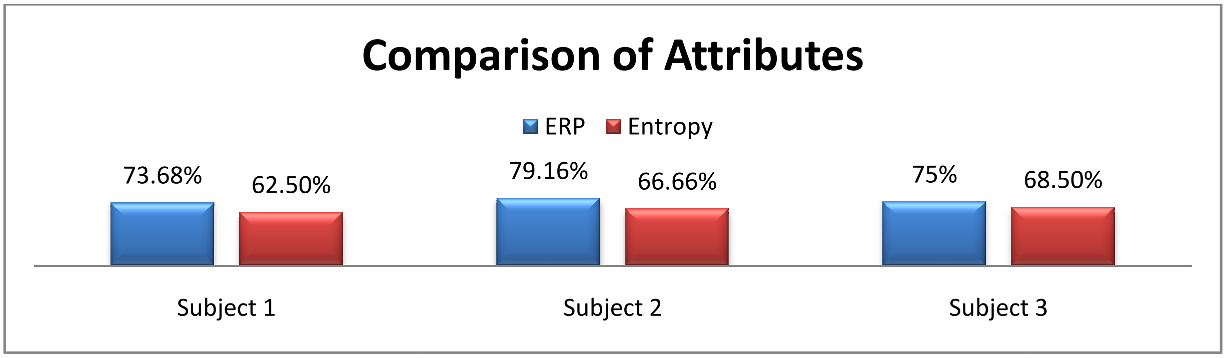

Figure 4:Comparison of ERP and Entropy attributes

It shows that highest accuracy of 79.16% is achieved for ERP attribute, 68.5% for Entropy extracted attribute.

8. Conclusion

In this paper, the comparison of different attributes namely Event related potential and Entropy has been performed. The accuracy of classification is consistently better in all three subjects for event related potential than entropy.It has been observed that ERP for subject 1, subject 2 and subject 3 is classified effectively with an accuracy of 73.68%, 79.16% and 75% respectively. Whereas accuracy achieved for Entropy for all the three subjects is not so good. Also emotions are classified using three subjects and two frontal electrodes. So scope could be widened by increasing the number of subjects and electrodes for classification of emotions.

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