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


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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 been acquired 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, N100), (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 expressions under 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 emotions were given by researchers like Darwin, Plutchik and Ekman. Plutchik considered that there are eight basic emotions such as surprise, 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 displeased was represented along y-axis. The emotion describing words were so arranged that the like meaning words were closer while the opposites was arranged 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.

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2. Review

Picard, R. [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, Photoplethysmograph, 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 dataset for 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 using Mahalanobis 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 table 1.
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 were 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, narrowband, higher order crossing and wavelet entropy were 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 eNTERFACE06 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 been collected 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 namely F3, F4 and Fz have been used for classification. Emotions have been evoked by stimulating the subject with images provided by International affective picture System (IAPS). These images from IAPS were collected at university of Florida by the scientifics of National Institute of Mental Health Center for

Table 1: The classification accuracy achieved using different classifiers

<table>
<thead>
<tr>
<th>Classifier</th>
<th>HVHA (%)</th>
<th>HVLA (%)</th>
<th>LVHA (%)</th>
<th>LVLA (%)</th>
<th>Total (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mahalanobis distance</td>
<td>85.71</td>
<td>82.14</td>
<td>78.57</td>
<td>71.43</td>
<td>79.46</td>
</tr>
<tr>
<td>Support Vector Machine</td>
<td>85.71</td>
<td>85.71</td>
<td>71.43</td>
<td>82.14</td>
<td>81.25</td>
</tr>
</tbody>
</table>

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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 are of different categories such as nature, love, baby, snake, grave etc. Every image is shown to subject for 1 second followed by plus symbol for 1.5 seconds. 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 preprocessed in 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 50 Hz has been used to remove any power noise interference.

Figure 3 the preprocessed EEG signals for one of the subjects.

4. Feature extraction

The filtered data has been used for feature extraction. The ERP potentials namely P100, PT100, N100 and NT100 are extracted for each class of emotions from the acquired EEG signal.

P100 is the maximum going peak observed between 80 ms to 120 ms after the onset of stimuli, so P100 is known as maximum ERP of participant in the time limit of 80 to 120 ms. PT100 is the latency which corresponds to the time (in ms) when P100 occurs. N100 is minimum potential observed between 80 ms to 120 ms after the onset of stimuli, so N100 is known as the minimum ERP of the participant in the time limit of 80 to 120 ms. Similarly NT100 is the latency which corresponds to the time (in ms) when N100 occurs.

5. Classification & Results

The extracted attributes have 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 overfitting 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 at F3 electrode for 11 attributes combinations

<table>
<thead>
<tr>
<th>Subjects</th>
<th>P100-Pt100 (%)</th>
<th>P100-N100 (%)</th>
<th>P100-Nt100 (%)</th>
<th>Pt100-N100 (%)</th>
<th>N100-Nt100 (%)</th>
<th>N100-Pt100 (%)</th>
<th>P100-Pt100-Nt100 (%)</th>
<th>P100-Pt100-N100 (%)</th>
<th>P100-N100-Nt100 (%)</th>
<th>P100-Pt100-N100-Nt100 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject 1</td>
<td>52.63</td>
<td>57.89</td>
<td>68.42</td>
<td>57.89</td>
<td>63.15</td>
<td>57.89</td>
<td>73.68</td>
<td>73.68</td>
<td>57.89</td>
<td>52.63</td>
</tr>
<tr>
<td>Subject 2</td>
<td>62.5</td>
<td>54.16</td>
<td>66.66</td>
<td>62.5</td>
<td>58.3</td>
<td>70.8</td>
<td>66.66</td>
<td>62.5</td>
<td>66.66</td>
<td>58.3</td>
</tr>
<tr>
<td>Subject 3</td>
<td>58.33</td>
<td>63.5</td>
<td>66.66</td>
<td>68.32</td>
<td>62.5</td>
<td>58.33</td>
<td>54.16</td>
<td>70.8</td>
<td>66.66</td>
<td>62.5</td>
</tr>
<tr>
<td>Subject 4</td>
<td>53.84</td>
<td>46.15</td>
<td>53.84</td>
<td>59.83</td>
<td>63.33</td>
<td>57.69</td>
<td>57.69</td>
<td>61.5</td>
<td>53.8</td>
<td>57.6</td>
</tr>
<tr>
<td>Subject 5</td>
<td>66.66</td>
<td>57.14</td>
<td>61.90</td>
<td>61.90</td>
<td>66.66</td>
<td>76.19</td>
<td>66.66</td>
<td>61.90</td>
<td>66.66</td>
<td>57.80</td>
</tr>
</tbody>
</table>

It can be seen from table 2 that at F3 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 obtained for 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 11 attributes combinations

<table>
<thead>
<tr>
<th>Subjects</th>
<th>P100-Pt100 (%)</th>
<th>P100-N100 (%)</th>
<th>P100-Nt100 (%)</th>
<th>Pt100-N100 (%)</th>
<th>N100-Nt100 (%)</th>
<th>N100-Pt100 (%)</th>
<th>P100-Pt100-Nt100 (%)</th>
<th>P100-Pt100-N100 (%)</th>
<th>P100-N100-Nt100 (%)</th>
<th>P100-Pt100-N100-Nt100 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject 1</td>
<td>57.8</td>
<td>57.89</td>
<td>66.66</td>
<td>67.89</td>
<td>63.15</td>
<td>68.4</td>
<td>57.8</td>
<td>52.6</td>
<td>63.15</td>
<td>57.8</td>
</tr>
<tr>
<td>Subject 2</td>
<td>62.5</td>
<td>66.66</td>
<td>79.16</td>
<td>62.5</td>
<td>62.5</td>
<td>54.16</td>
<td>75</td>
<td>62.6</td>
<td>66.66</td>
<td>62.5</td>
</tr>
<tr>
<td>Subject 3</td>
<td>62.5</td>
<td>70.88</td>
<td>62.5</td>
<td>70.83</td>
<td>58.33</td>
<td>75</td>
<td>62.6</td>
<td>66.66</td>
<td>68.26</td>
<td>62.5</td>
</tr>
<tr>
<td>Subject 4</td>
<td>76.92</td>
<td>69.23</td>
<td>65.38</td>
<td>65.38</td>
<td>61.5</td>
<td>65.38</td>
<td>57.69</td>
<td>65.38</td>
<td>61.5</td>
<td>69.23</td>
</tr>
<tr>
<td>Subject 5</td>
<td>66.66</td>
<td>61.90</td>
<td>71.4</td>
<td>57.14</td>
<td>71.42</td>
<td>66.66</td>
<td>61.9</td>
<td>57.14</td>
<td>61.9</td>
<td>57.14</td>
</tr>
</tbody>
</table>

The best accuracy has been achieved along 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.

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Among the eleven attribute combinations used in this study, the best accuracy achieved for attribute combination is for attribute combination of P100, Nt100. For subject 3 the best accuracy achieved for attribute combination (P100, Pt100, N100, Nt100) and (P100,N100,Nt100)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.

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

<table>
<thead>
<tr>
<th>Subjects</th>
<th>P100-Pt100 (%)</th>
<th>P100-N100 (%)</th>
<th>P100-Nt100 (%)</th>
<th>Pt100-N100 (%)</th>
<th>N100-Pt100 (%)</th>
<th>P100-Pt100-N100 (%)</th>
<th>Pt100-Pt100-Nt100 (%)</th>
<th>P100-N100-Nt100 (%)</th>
<th>P100-Pt100-N100-Nt100 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subject 1</td>
<td>52.63</td>
<td>52.63</td>
<td>68.42</td>
<td>57.89</td>
<td>63.15</td>
<td>57.89</td>
<td>63.15</td>
<td>63.15</td>
<td>57.89</td>
</tr>
<tr>
<td>Subject 2</td>
<td>62.5</td>
<td>58.33</td>
<td>62.5</td>
<td>62.5</td>
<td>66.66</td>
<td>58.33</td>
<td>62.5</td>
<td>70.83</td>
<td>62.5</td>
</tr>
<tr>
<td>Subject 3</td>
<td>62.5</td>
<td>70.88</td>
<td>58.33</td>
<td>62.5</td>
<td>66.66</td>
<td>58.33</td>
<td>61.5</td>
<td>62.5</td>
<td>66.66</td>
</tr>
<tr>
<td>Subject 4</td>
<td>61.5</td>
<td>57.89</td>
<td>65.38</td>
<td>73.07</td>
<td>69.23</td>
<td>53.28</td>
<td>57.69</td>
<td>65.38</td>
<td>57.89</td>
</tr>
<tr>
<td>Subject 5</td>
<td>71.42</td>
<td>61.90</td>
<td>66.66</td>
<td>66.66</td>
<td>61.9</td>
<td>71.42</td>
<td>71.42</td>
<td>57.14</td>
<td>61.9</td>
</tr>
</tbody>
</table>

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,Nt100)is 70.8%. 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](image)

It can be seen that the best accuracy has been obtained 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; the attribute 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 signal for 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.

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7. Scope for Future Work
Since the emotions are classified under laboratory conditions, it is impossible to know the exact instance at which emotions have been evoked which is in fact a drawback. Furthermore only four attributes such as P100, Pt100, N100 and N100 are extracted for emotion classification. By considering more number of ERP features and subjects, the scope could be widened.

References

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