IJITKM Volume 7 • Number 2 Jan– June 2014 pp. 143-152 (ISSN 0973-4414)

Emotion Classification along Valence Axis Using ERP Signals

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Abstract
Emotions play a very crucial role in our daily life. It is the emotion by which one can express his/her feelings. Emotion can be seen in person's face in voice or in gesture such as reaction to stimuli. EEG signals play a significant role in knowing feelings or emotions of a person. This paper describes the extraction of event related potentials from the acquired EEG signals of three subjects by using the images from International affective Picture Systems for evocation of emotions. The event related potential features selected for emotion classification are P100, N100, P200, N200, P300 and N300 collected from three electrodes namely Cz, f3 and p4. The Support Vector Machine classifier has been used to classify the emotions into two classes along the valence axis. An accuracy of 95% is achieved on p4 electrode, 93.75% accuracy on f3 electrode and 92.5% accuracy is achieved on Cz electrode.

1. Introduction

Emotions are said to be very potential means for analyzing condition of mind. Emotions play an important role in human life. It is a way of expressing thought, views, and feelings. Some emotions are easily recognized by seeing face or listening to voice like happy, sad, excited, tensed, frustrated, and sleepy. Emotions can influence or change someone's behavior and mood easily both in a positive and a negative way. If emotion is defined biologically, than one can say that emotion is nothing but the hormone changes in the body which affect the body and can easily be recognized on face, voice and body movements. Kleinginna and Kleinginna analyzed 92 definitions of emotions [1].The reason why studying emotions is significant is that emotion is an important aspect in the interaction and communication between humans. There are two models for given by different researchers. The first model was proposed by Darwin and after that it was followed by Plutchik and Ekman [2]. Ekman said that all emotions can be composed of some basic emotions. Plutchik claims that there are eight basic emotions and all other emotions are derived from theses eight emotions. These eight emotions are sadness, disgust, surprise, anger, fear, joy, curiosity, and joy acceptance [3]. Ekman has chosen other emotions to be the basic emotions. He considered happiness, disgust, anger, fear, sadness and surprise as the basic emotions. Two classes of emotions is divided along X and Y axis in valence and arousal dimensions in which valence is divided along positive valence and negative valence while arousal is divided along excited and unexcited as shown in Fig.1.

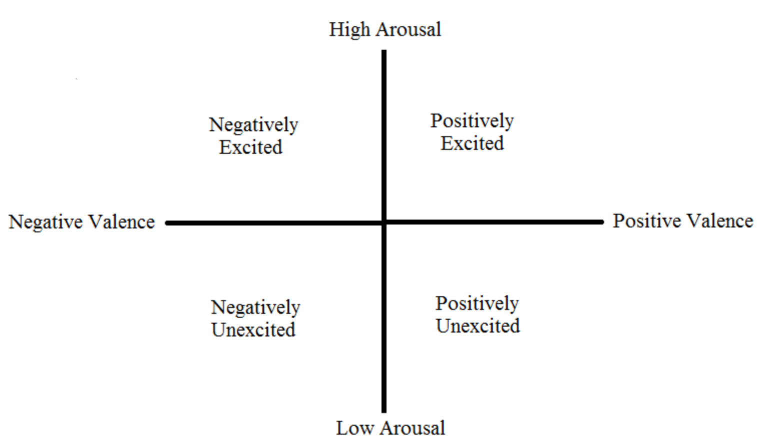

Fig.1 Arousal and Valence Axis

Recognition of emotions by physiological means is a subject of interest for both psychologists as well as engineers [4]. EEG can be used to detect emotions. Emotions cannot be classified directly from the signals, but require base line removal and processing of signals using various signal conditioning techniques. The features extracted from the processed EEG signals could be helpful in analyzing emotions. Emotions can be detected from other techniques also such as Functional Magnetic Resonance Imaging, Positron Emission Tomography but the best way is through EEG as it has simple and portable hardware, high temporal resolution, and direct measurement of electrical activity [5] [6]. Gaulin, Steven J. C. et al. suggested that the Physiology of emotion is closely linked to Arousal of the Nerves [7]. Most of the researchers have focused on facial expression recognition and speech signal analysis for assessing emotions [8, 9]. Healey, J. (2001) worked on the 8 emotional states namely no emotion, anger (High arousal negative valence), hate (Low arousal Negative valence), grief (High arousal negative valence or Low arousal Negative valence), love (Low arousal positive valence), romantic love (love for opposite sex (high arousal positive valence) and reverence (for nature and God by using guidelines mentioned by Clynes for evoking emotions [10]. Russell, J.A. (2003) discussed about the feelings like joy, happiness, fear, angry, depressed, displeasure and concluded that all were inter related. He worked on affective space model (Valence and Arousal) by representing them as a circle in a two dimensional space [11]. Frantzidis.C et al. (2010) in their research study described the classification of neurophysiological data for four emotional states obtained by viewing the emotional evocative pictures selected from International Affective Picture System (IAPS) [12]. He proposed twos step classification in which valence discrimination was performed first and after that arousal discrimination was performed. Classification was done by Mahalanobis distance (MD) and Support Vector Machine (SVM).The overall accuracy achieved for both the classes were 79.5% for MD and 81.3% for SVM [13]. Mandeep Singh et al. (2013) took the enterface data provided by Savran et al. (2006) [14] [15] [16] [17] for 3 participants and performed classification along valence axis by using the naïve bayes classifier on the extracted ERP features. The overall accuracy achieved for ERP feature was 56% and by changing the feature to STFT, accuracy obtained was 51%. Similarly with the PSD feature, accuracy was 56% and after combining all the three features accuracy obtained was 64% which was comparatively high among all [18], while the overall accuracy achieved for 3 participants by using Artificial Neural Network was 76.59% [19]. Frantzidis.C et al. (2008) used physiological signals from skin conductance and central nervous system and used Neural Network classifier for classification along arousal axis. The classification results obtained for emotion state Joy - 80%, Fear- 100%, Happiness- 80%, and Melancholy – 70% [20].

2. MP 150 System

Data is acquired by using EEG Cap which has 20 electrodes used in bipolar embedded in it. The placement of electrodes on EEG Cap is done through 10-20 system of placement of electrodes. The electrodes are attached to BIOPAC MP150 amplifiers. The ear lobe or the mastoid is used as a reference electrode. The EEG signals coming from the electrodes are acquired by the Acqknowledge 4.2 software [21] which is provided by BIOPAC MP150 [22].

3. Data Collection

The data is collected from three male participants. All the subjects are right handed and suffered from no medical ailment. The EEG signal is collected from three electrodes namely Cz, f3 and p4 where Cz is the central electrode, f3 is known as the frontal electrode and p4 is placed in the parietal zone. The stimuli for evoking emotions used are the images of International Affective Picture System provided by NIHM centre of the University of Florida [12]. Total of 80 images are shown to the participant and all are related to valence and arousal axis. The stimulus is pre stimulus and post stimulus. One image is the white cross with black ground and second stimulus is the image related to emotions. Each image is visible to the subject for 1 sec and image with the white cross and black ground is shown for 1.5 second. Acquisition of the data is done at the sampling rate of 500 Hz [23]. An EEG signal is collected by using the acqknowledge software provided by BIOPAC. The classification is done along valence axis as all the images used are of high arousal. The collected EEG are used to extract event related potential (ERP) feature.

4. Signal Conditioning

After the acquisition of EEG signals, signal conditioning is a very important part which should be performed in order to get better results. The EEG signals may contain some interference such as noise and artifacts and this interference should be removed to get better results. Acqknowledge software is very helpful while applying filter operations. Filtered operations present in acqknowledge software are digital IIR filters, adaptive filters, comb band stop filter. The acquired EEG signals are filtered using a low pass filter with a bandwidth of 40 Hz to remove noise and artifacts. A high pass filter with a cut off frequency of 0.5Hz is used to obtain a signal in the desired frequency range of 0.5 – 40 Hz. The comb band stop filter is used to eliminate the power noise at a frequency of 50 Hz and its harmonics. Fig. 2 shows the EEG signal obtained after signal conditioning.

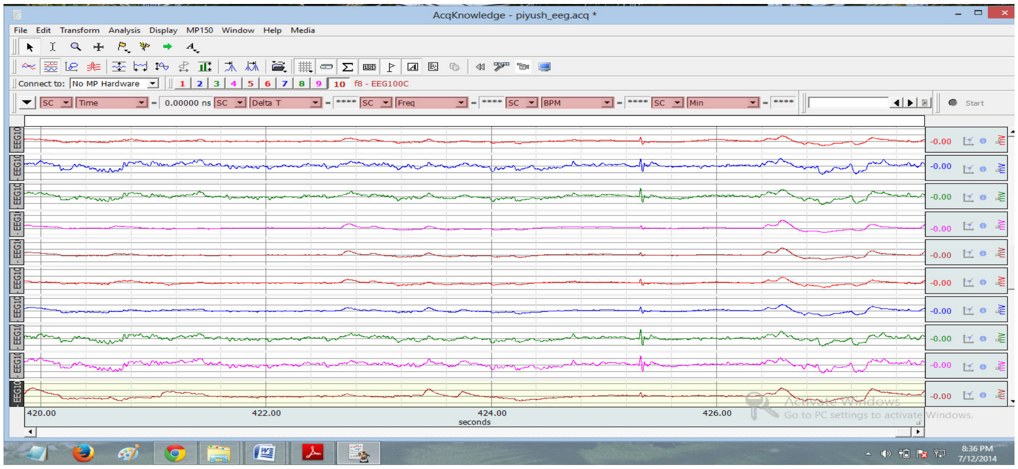

Fig.2 Signal Conditioning of EEG Signal

5. Feature Extraction

The features that are extracted from EEG signals are P100, N100, P200, N200, and P300 and N300.P100 which is also called the P1 the first positive peak observed between 80 and 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.For the equivalent electrode, the P100 of the subject is determined through software. N100 is just the reverse of P100. Here the minimum of ERP that is N100 value is chosen as an attribute for classification. The N100 value is also determined between the time limit of 80 and 120ms. P200 is a second positive peak observed about 200ms, varying from 180 to 220ms. N200 is a negative-going wave that also peaks from 180-220ms P300 is a positive peak observed at 300 ms, varying between 280 and 320ms. The features extracted for P100 and N100 is between the time limit of 80-120 ms and for P200-N200 the time limit is 180-220ms and similarly for P300-N300 value the time limit range is 280-320ms. The ERP values are shown below in Fig.3

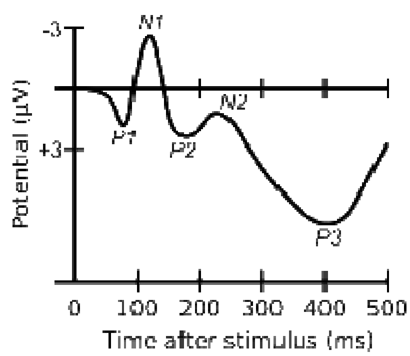

Fig.3 Event Related Potential [24]

6. EEG Classification:

A classifier is a system which divides the data into different classes and gives relationship between the extracted feature and the emotion related to the subject under observation. To know which emotions are present in the signal, classification of the signal is done. Classification is done with the help of Support Vector Machine into two classes namely low valence high arousal and high valence low arousal.

7. Results

From the Classification technique, we classified the extracted data into two classes that is high valence and low valence using a Support Vector Machine (SVM) classifier. Extracted features from ERP in different combinations are used to analyze the accuracy of data. MATLAB Tool is used for classifier and high polynomial order is taken. The polynomial order is taken from 10 to 16.Though the higher polynomial is taken but it is not necessary that it always show higher accuracy for each subject. Higher accuracy can be achieved by lower order polynomial also. Accuracy depends on the ERP feature extraction and classifier used. SVM classifier used in this study. The results for higher order polynomial from 10 to 14 are shown from Fig.4 to Fig.10.

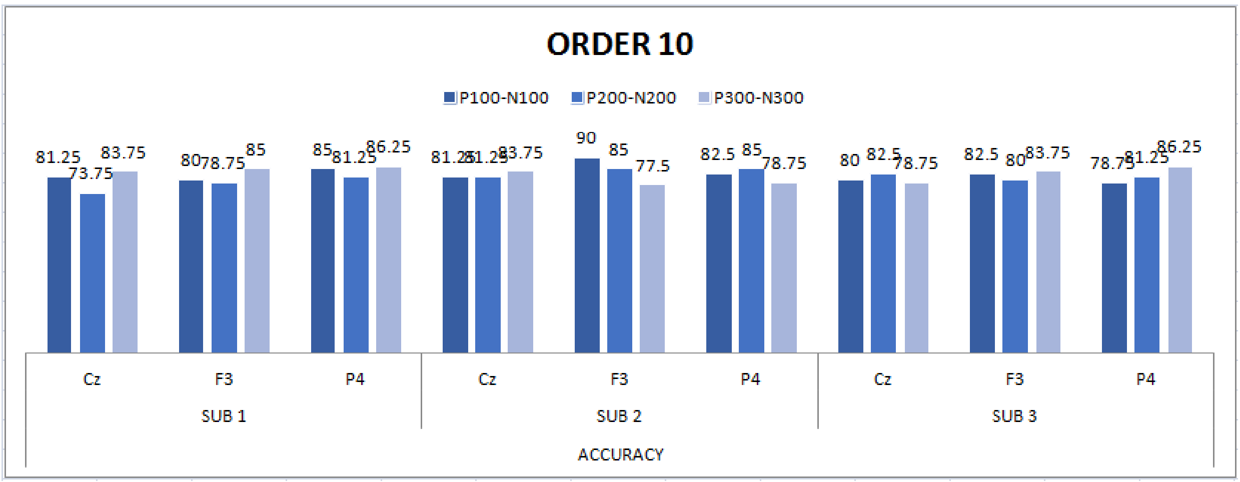

Fig.4 Accuracy of 3 participants on 3 electrodes for Order 10

While taking P100-N100 features of ERP as attributes to SVM with a polynomial order of 10 an accuracy of 81.25% is obtained on Cz electrode, 80% accuracy for f3electrode, 85% accuracy for p4 electrode for subject 1,similarly for the same attributes 81.25% accuracy is achieved on Cz electrode, 90% for f3 electrode and 82.5% for p4 electrode for subject 2 and for subject 3, an accuracy of 80% is obtained on Cz electrode followed by 82.5% for f3 and 78.79% for p4 electrode.

However when P200-N200 attributes are used for classification, 73.75% accuracy is obtained on Cz electrode, 78.75 % accuracy on f3 electrode and 81.25% accuracy on p4 electrode for subject 1, while 81.25% accuracy is obtained on Cz electrode, 85% accuracy on f3 electrode and 85% on p4 electrode for subject 2 and for subject 3 82.5% accuracy on Cz electrode, 80% accuracy for f3 electrode, 81.25% accuracy is achieved on p4 electrode.

For P300-N300 attributes the accuracy obtained is 83.75% accuracy on Cz electrode, 85 % accuracy at f3 and 86.25% accuracy for p4 electrode for subject 1, similarly 83.75% accuracy on Cz electrode, 77.5% accuracy for f3 electrode and 78.75% for p4 electrode for subject 2 and for subject 3, 78.75% accuracy on Cz electrode, 83.75% accuracy for f3 electrode and 86. 25% accuracy for p4 electrode is achieved.

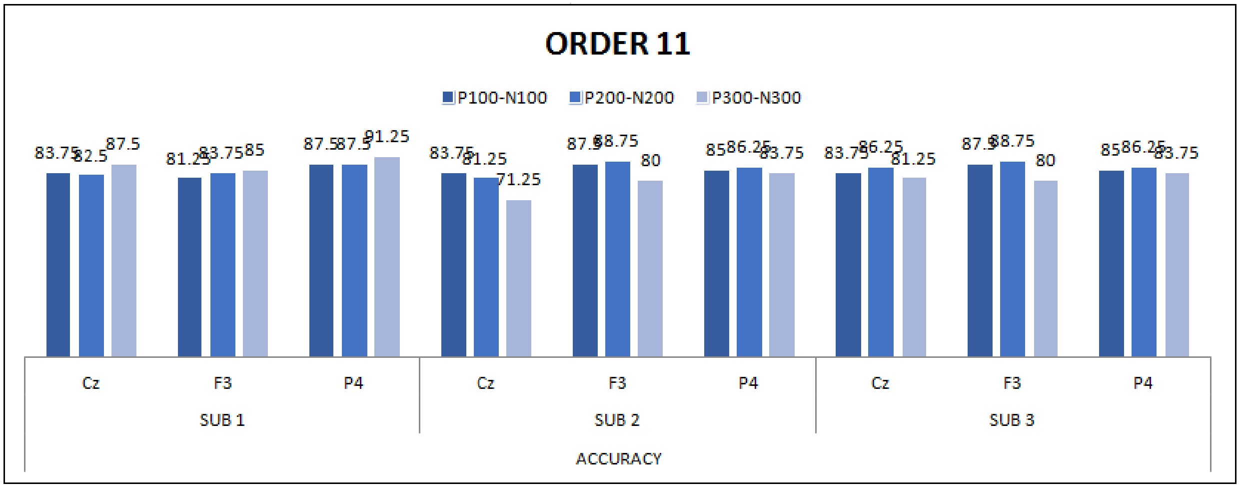

Fig.5 Accuracy of 3 participants on 3 electrodes for Order 11

Similarly the charts shown in figures 5, 6, 7, 8, 9 and 10 shows the accuracies obtained for the three subjects on ERP features when different polynomial orders are taken for emotion classification.

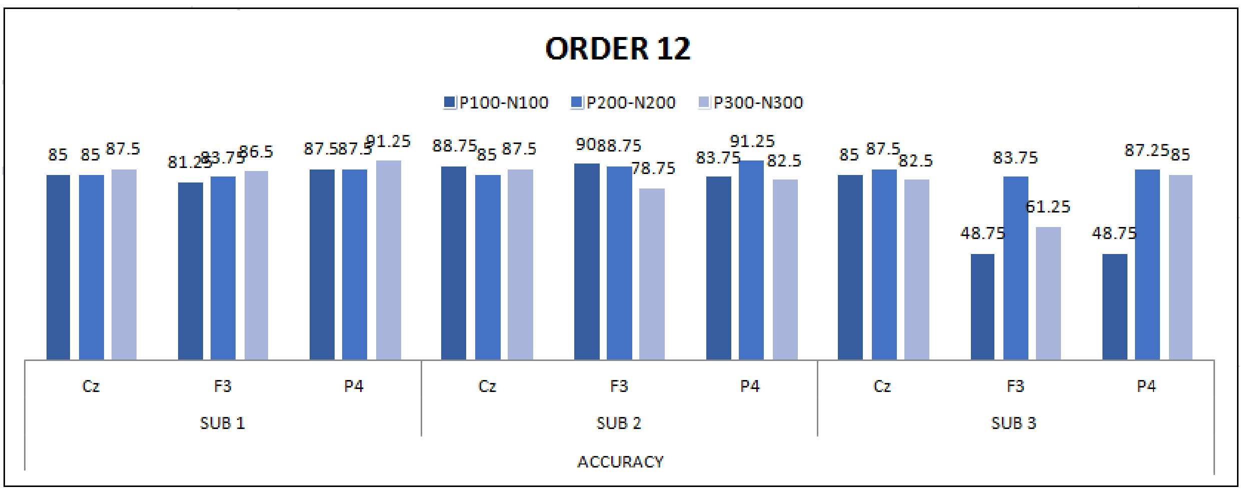

Fig.6 Accuracy of 3 participants on 3 electrodes for Order12

Subject 2 showed consistently higher accuracies of 90% on f3 electrode of all the three electrodes for the selected p100-n100 attributes.

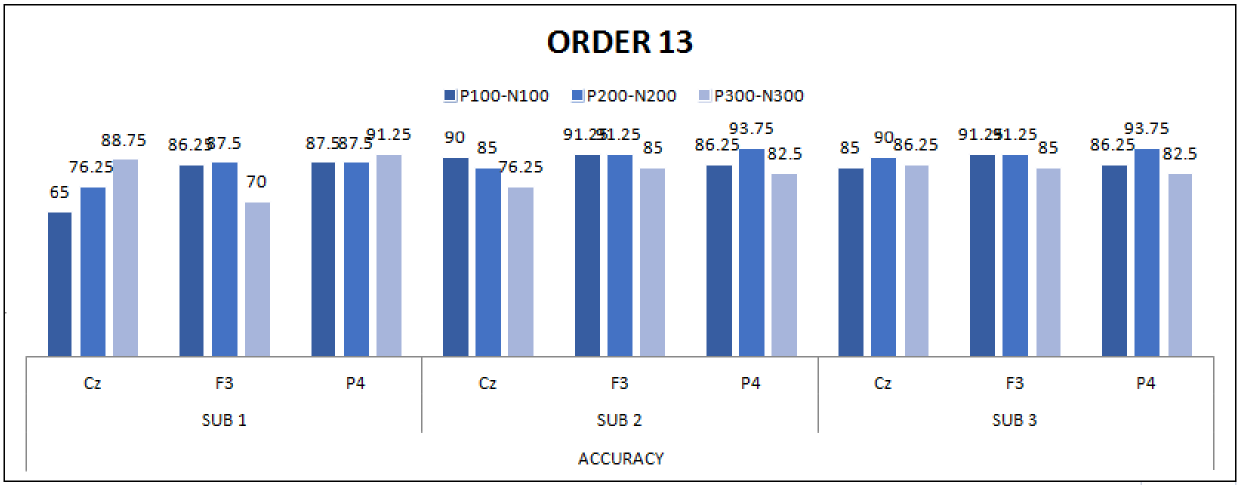

Fig.7 Accuracy of 3 participants on 3 electrodes for Order 13

While taking P100-N100 features of ERP as attributes to SVM with a polynomial order of 13, an accuracy of 65% is obtained on Cz electrode comparatively smaller as compared to the polynomial orders 10, 11 and 12. Similarly on classification with P200-N200 attributes, the accuracy shows a lower trend as compared to the subjects 2 and 3 for the same polynomial order.

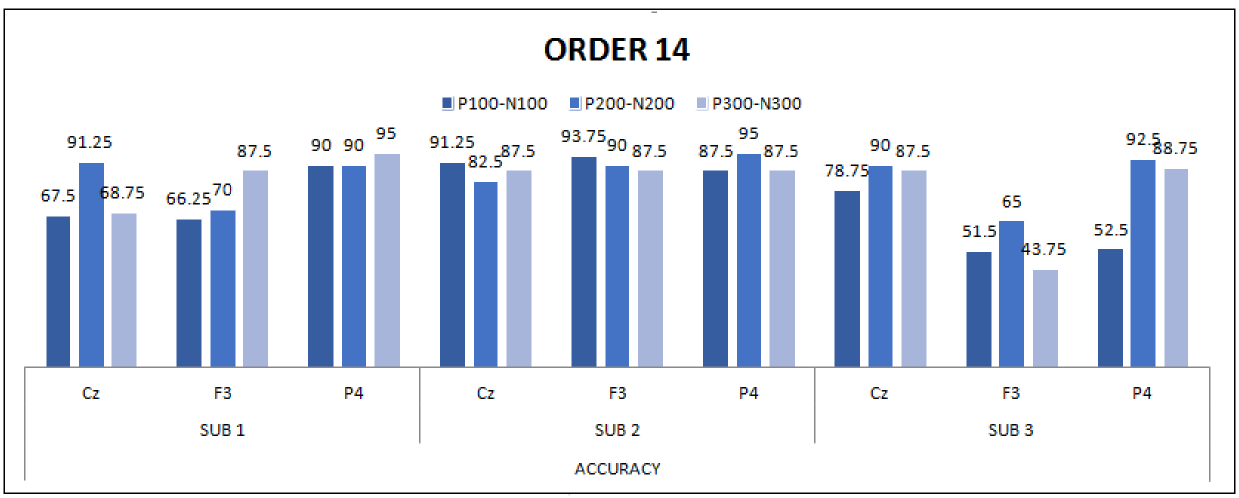

Fig.8 Accuracy of 3 participants on 3 electrodes for Order 14

On classification with a polynomial order of 14, lower accuracies are obtained on F3 electrode of subject 3. While using P100- N100 attributes for classification with this polynomial order, lower accuracies are obtained on Cz and F3 electrodes of subject 1 and F3 and P4 electrodes for subject3. Subject 2 shows consistently higher accuracies on the three electrodes for the selected attributes. Higher accuracies are consistently obtained on P4 electrodes of the three subjects on the acquired ERP features.

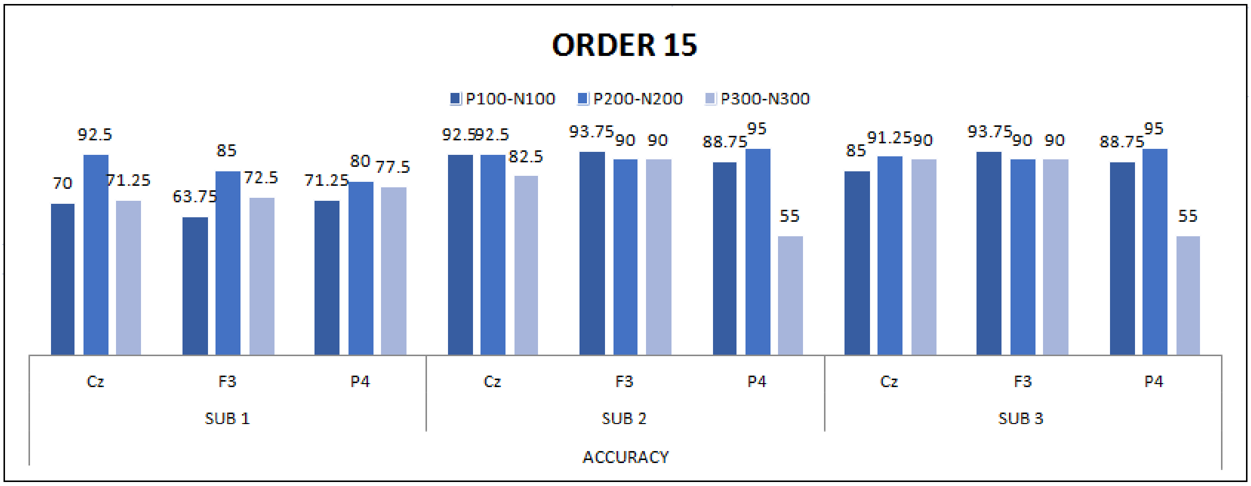

Fig.9 Accuracy of 3 participants on 3 electrodes for Order 15

Good results are obtained on almost all the electrodes except for P300-N300 ERP features. The accuracy as high as 95 % is obtained on P4 electrode.

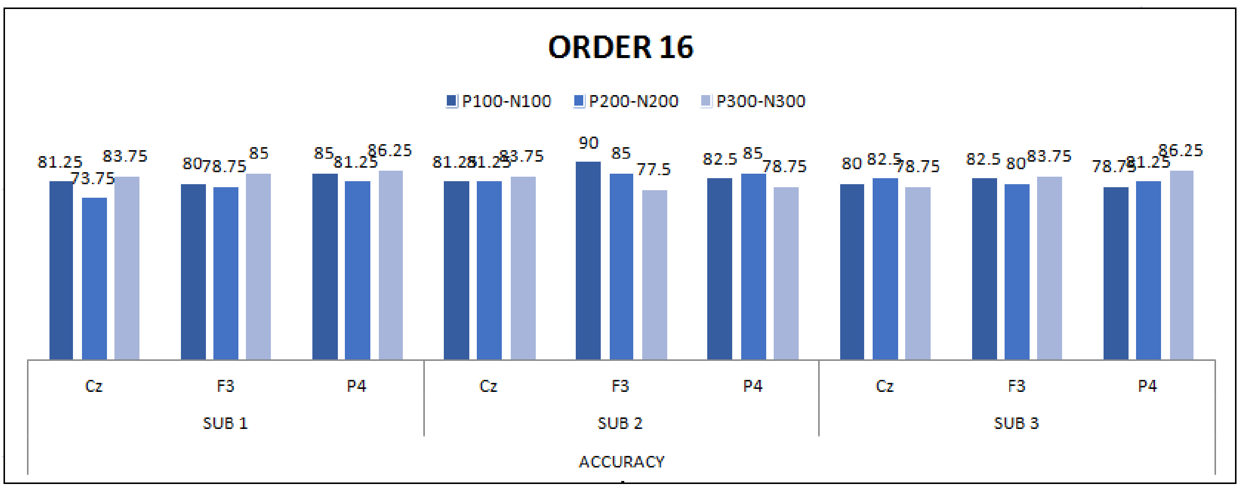

Fig.10 Accuracy of 3 participants on 3 electrodes for Order 16

At this polynomial order, the accuracy remains high on all the three electrodes for the three subjects under observation.

To perform the subject wise analysis for classification of emotions, the figures 11, 12 and 13 are shown herein for different polynomial orders.

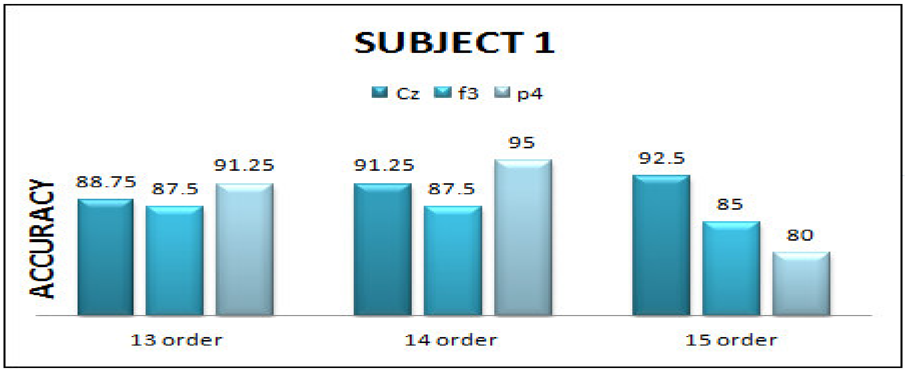

Fig.11 Accuracy of Subject 1 for all 3 electrodes

From Fig.11 it can be seen that the best results are obtained at polynomial order 14 on all the selected 3 electrodes for subject1.

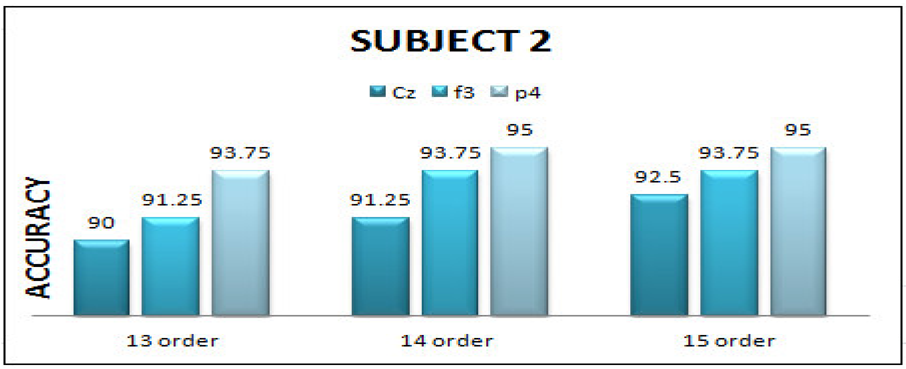

Fig.12 Accuracy of Subject 2 for all 3 electrodes

Fig.12 also asserts that when using polynomial order 14, better results are obtained for subject 2 with P4 electrode topping the table by displaying higher accuracies. Even good results are obtained at polynomial order 15.

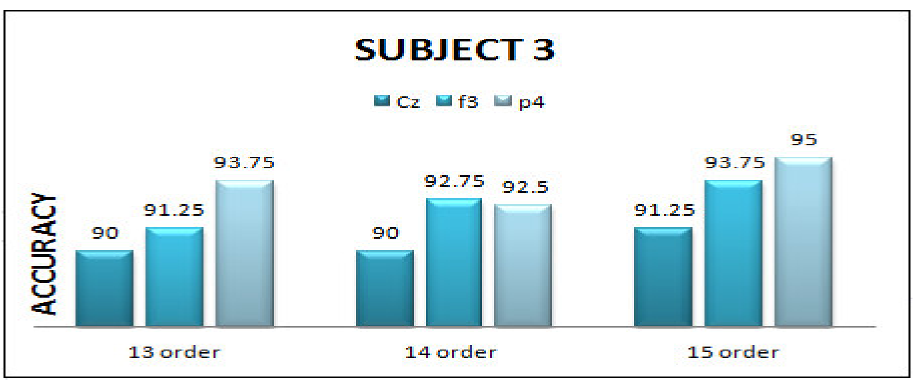

Fig.13 Accuracy of Subject 3 for all 3 electrodes

Lower accuracies are obtained for subject 3 on polynomial orders other than polynomial order 15. P4 electrode again tops the chart by displaying higher accuracies at almost all the polynomial orders.

8. Conclusion

In this work data is acquired for emotion classification along valence axis that is positive valence and negative valence. The electrodes chosen are Cz, f3, p4. Data is acquired at the sampling rate of 500Hz.The data collected is used for extracting ERP features and after that features are classified using SVM. The highest accuracy obtained on p4 electrode is 95%, 93.75 % on f3 electrode and 92.5% accuracy on Cz electrode. It can be concluded from the obtained results that accuracy in emotion classification is proportional to the polynomial order of SVM classifier. Lower order gives lower accuracy and after increasing the order, accuracy automatically increases for the ERP features. From the considered electrodes for emotion classification, P4 electrode top the chart for almost all polynomial orders used for classification of emotions. Though, the two classes of emotions could be classified with 95% accuracy, decreasing the polynomial order still remains a challenge [21]. Moreover, only three electrodes are used for classification, so the horizon could be widened in future by working on more number of electrodes.

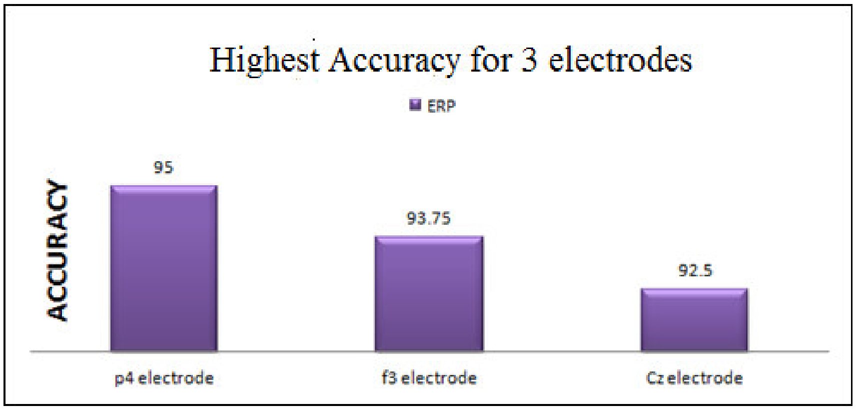

Fig. 14 Accuracy of all 3 electrodes for 3 Electrodes

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