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Emotion Recognition along Valence Axis Using Naïve Bayes Classifier

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ABSTRACT

Emotion is an important aspect in the interaction between humans. It is fundamental to human experience and rational decision-making. There is a great interest for detecting emotions automatically. A number of techniques have been employed for this purpose using channels such as voice and facial expressions. However, these channels are not very accurate and can be faked. In this paper, we have used EEG signals for emotion detection. For this, two different emotions from EEG signals are inferred that are unpleasant and pleasant. This will require using sophisticated feature selection techniques like Power Spectral Density (PSD), Short Time Fourier Transform (STFT) and Event Related Potential (ERP) that generates a large set of features on the basis of time- frequency domain. The features have been collected from the raw data available at Enterface 06 website. Naïve Bayes classifier has been used to classify the emotions in two classes Low Valence and High Valence. For classification through Naïve bayes, with ERP as a feature the classifying accuracy of **56%** is obtained**,** with STFT as a feature determined from 3 participants, the accuracy obtained is **51%.** Similarly with PSD as a feature the accuracy achieved is **56%.** Finally, on combining the entire data of STFT and PSD of all 3 participants, we obtained better accuracy of about **64%.**

INTRODUCTION

An emotion is a mental and physiological state associated with a wide variety of feelings, thoughts, and behavior. It is a subjective experience depending on individual to individual basis and his past experiences, which makes studying emotions one of the most difficult and very open field of research. There are more than 90 definitions of "emotion" and there is little consensus on the meaning of the term [1]. The reason why studying emotions is important is the fact that emotion is an important aspect in the interaction between humans. There are two models for theoretical emotion representation. The first model that is proposed by Darwin and after that followed by Plutchik and Ekman [2]. Ekman used the idea that all emotions can be composed of some basic emotions exactly like the white color can be composed of primary colors. Plutchik claims that there are eight basic emotions which all other emotions can be derived from. These eight emotions are anger, fear, sadness, disgust, surprise, curiosity, acceptance and joy. Ekman has chosen other emotions to be the basic emotions. He considered anger, fear, sadness, happiness, disgust and surprise as the basic emotions.

The second model as shown in Figure 1.1 represents emotion is the dimensional view model. It describes each emotion on a multidimensional scale. The first dimension is emotional valence, with positive emotions on one side and negative emotions on the other side. The second dimension represents the arousal. This model is used in most of the studies because of its simplicity and universality and there is little controversy about the two dimensions of the model.

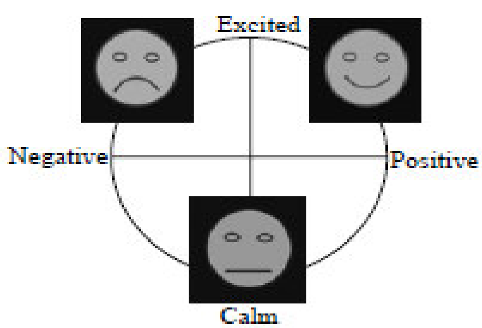

Figure 1.1: Two dimensional view of emotion [3]

This is a two-dimensional model, with valence and arousal being the horizontal and the vertical axes, respectively. Valence ranges from negative to positive (or unpleasant to pleasant), whereas arousal ranges from inactive (or calm) to active (or excited). In case the third dimension is ignored the emotion can be quantized into four quadrants from the image set. The different emotional states of humans can be appropriately placed within four quadrants. 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[4]. Christos et al (2010) in his 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). He adopts the independency of two emotional dimensions, namely arousal and valence. He considered two step classification procedures for discrimination of emotional states between EEG signals. First classification involves arousal discrimination then valence discrimination was performed. With the help of Mahalanobis (MD) and support vector machines (SVMs) emotions were discriminated. After performing these operations he got the overall accuracy of 79.5% and 81.3% for MD and SVM respectively [5].Implicit assessment of emotion can be carried out by considering human expressions and physiological reactions. In first case, the human expression can be analyzed by using his images and taking the sample of his voice resulting due to a particular emotional stimulus. Then the emotional estimation can be performed using images and signal processing techniques. The analysis using physiological variables is gaining a lot of popularity nowadays. The common physiological variables being considered for emotion quantification are Galvanic Skin Resistance (GSR), Blood Pressure (BP), and Heart Rate (HR) etc. Thereafter the emotions can be classified using statistical methods and Naïve Bayes classifier technique as an input to these classifiers different attributes extracted from gathered data can be used. Generally, physiological signals originate from the central nervous system (CNS) and the peripheral nervous system (PNS). Regarding the signals from the CNS, brain electrical activity has gained great interest for studying emotions. Among other physiological signals, EEG has gained special interest because emotion is considered as a psychological process which is directly related to brain activities.

DATA COLLECTION

In the current study, as emotions we explore the EEG changes during different emotional states based on subjective and subject-independent analysis. The analysis has been done on the EEG data available on the Enterface website [6]. The data was collected from five participants i.e. all are male as well as right handed. The emotions were elicited by using the stimulus provided by NIMH center of the University of Florida called International Affective Picture System (IAPS) [7]. The participants were also asked to rate the images on the arousal and valence scale using self assessment manikin method (SAM) [8]. This work shows that the participants were shown the images from IAPS based on three classes namely clam, positive exiting, and negative exiting. The data has been digitized and processed upon by using the open source software called EEG LAB [9].

The images shown for calm had a mean arousal value of less than 4 and mean valence value between 4 to 6, while the stimuli for positive exciting had a mean valence greater than 6, variance valence smaller than 2 and mean arousal greater 5, and for exciting negative the images had mean valence should smaller than 3 and mean arousal greater than 5.

Calm: Mean Arousal < 4
4 < Mean Valence < 6
Exciting Positive: Valence > 6.8
Variance (Valence) < 2
Mean Arousal > 5
Exciting Negative: Mean Valence < 3
Mean Arousal > 5

Each image was shown for 2.5 seconds and total of 5 images for evoking one emotion were shown at a time. So to evoke one emotion the EEG data was collected for 12.5 seconds. The EEG data was collected at a sampling rate of 1024 Hz in the three sessions for each participant and the image sets were shown in a random order. To reduce the data set, the EEG data for participants 3, 4, and 5 down-sampled at a sampling rate of 256 Hz. The attributes have been determined from the seven EEG electrodes Cz, Pz, Fz, FC1, FC2, F1, and F2 to classify the emotions in two classes high valence (Positive) and low valence (Negative).

FEATURE EXTRACTION

The processed data from EEG Lab has been used to extract the features. For feature extraction, we determined the Power Spectrum Density (PSD).We considered the PSD in different time frequency domain. In this frequency domain we extracted the maximum and minimum PSD according to different EEG frequency bands (delta, theta, alpha, beta and gamma).

Short Time Fourier Transform (STFT) features were extracted using FFT function by applying the discrete FFT to the signal and then finding its spectrum. EEG signals are non-stationary that means its spectrum changes with time such a signal can be approximated as piecewise stationary, a sequence of independent stationary signal segment. In STFT we determine the mean in different EEG frequency bands [10].

Another feature used for classification is Event Related Potential (ERP) P100, N100, P200, N200, and P300. P100 it is also called P1 as it first positive peak observed between 80 and 120ms after the onset of stimuli, here considered P100 as the maximum ERP of the subject in the time limit of 80 to 120ms. For the corresponding electrode, the P100 of the subject was determined manually. N100 it just reverses of P100. Here the minimum of ERP value was chosen as an attribute for classification. The N100 was also classified between the time limit of 80 and 120ms. P200 is a second positive peak observed about 200ms, varying from 150 to 275ms. N200 in particular is a negative-going wave that peaks 200-350ms post-stimulus and is found primarily over anterior scalp sites. P300 is a positive peak observed at 300 ms, varying between 250 and 500ms [11].

Hence, the goal of the current study is to investigate how different EEG sub-bands Delta 0-4hz, Theta 4-8hz, Alpha 8-12hz, Beta 12-30 hz, and Gamma above 30hz and regions are affected by different emotional states, considering specific characteristics of the signals that are captured by features both in time and frequency domains [14] [15] [16].

CLASSIFICATION

The extracted features were used as an input to the classifier to classify the emotions in high valence and low valence using Naïve Bayes classifier. The Naïve Bayes algorithm is based on conditional probabilities. It used Bayes' theorem, a formula that calculates a probability by counting the frequency of values and combinations of values in the historical data. It finds the probability of an event occurring given the probability of another event that has already occurred [17].

In various combinations, we used extracted features of EEG signal using PSD, STFT and ERP techniques as an input to Naïve Bayes classifier to classify the emotions [18] [19].

Posterior = (prior * likelihood)/evidence

For events r and s, bayes rule is:

$$p(r,s) = p(r \cap s) = p(r|s)p(s) = p(s|r)p(r)$$

$$p(\bar{r}|s)p(s) = p(s|\bar{r})p(\bar{r})$$

$$p(r|s) = \frac{p(s|r)p(r)}{p(s)} = \frac{p(s|r)\,p(r)}{\sum_{x=r,\bar{r}} p(s|x)p(x)}$$

RESULTS

By using classification technique, we classified the extracted data into two classes i.e, high valence or positive or 1 and low valence or negative or 0. In this, we used the extracted features from STFT, PSD and ERP in different combinations to analyze the difference in accuracy of data. First we used the ERP features of EEG signal and the accuracy around **56%** was observed. Then with STFT features the classification rate stood at **51%**, while with PSD features alone accuracy obtained was **56%**. So, finally we tried combining STFT and PSD features to obtain the accuracy. On training the classifier, the accuracy obtained was **64%** comparatively higher than others.

Features	Accuracy
ERP	56%
STFT	51%
PSD	56%
STFT + PSD	64%

Figure 1.2 Table of Accuracy obtained using Naïve Bayes Classifier

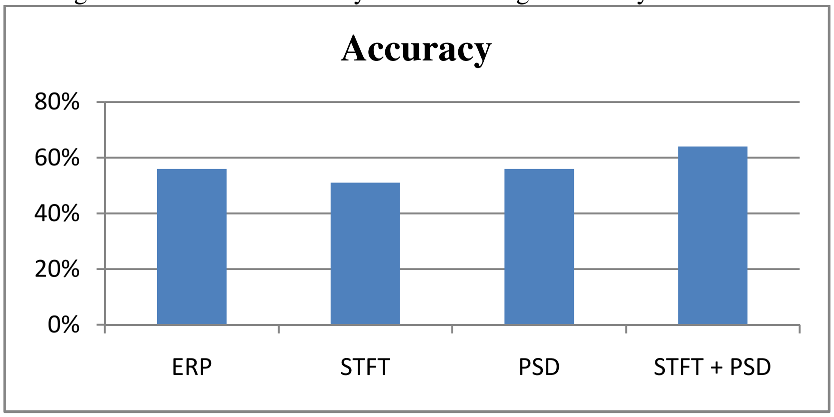

Figure 1.3 Graph depicting accuracy for selected features.

CONCLUSION

In this work, we used psychological data to classify and determined the accuracy for the quantification of emotions in two classes using Naïve bayes classifier. We used 3 participants data that is calculated at 7 electrodes namely Cz, F1, F2, FC1, FC2, Fz, Pz at a frequency scale of 256 Hz. We observed that psychological EEG data can also be easily grouped into relative emotional classes. On validating the unknown test data with the known training data accuracy of about **56%** is observed and on validating the known test data with known training data accuracy of about **60%** is observed. The high accuracy rate can be obtained by using PSD and STFT analysis for quantification of emotions. Further on this data, the accuracy obtained was higher as compared to that of Robert's Horling's work.

This research validates that emotion is a very much a personal matter as it depends upon the individual and his past experiences. This is a very good scope of improving upon these results by gathering the data a fresh on more number of participants and using Artificial Intelligence Technique for classification.

REFERENCES

[1] Robert Horlings, "Emotion recognition using brain activity", Man-Machine Interaction Group TU Delft 27 March 2008.

[2] P. Ekman, W.V. Friesen, M. O'Sullivan, A. Chan, I. Diacoyanni-Tarlatzis, K. Heider, R.Krause, W.A. LeCompte, T. Pitcairn, and P.E. Ricci-Bitti, "Universals and Cultural Differences in the Judgments of Facial Expressions of Emotion," J. Personality and Social Psychology, vol. 53, no. 4, pp. 712-717, Oct. 1987.

[3] http://upload.wikimedia.org/wikipedia/commons/thumb/8/84/Emotions.gif/220pxEmotions.gif.

[4] Glenn F. Wilson, Christopher A. Russell, "Real-Time Assessment of Mental Workload Using Psychophysiological Measures and Artificial Neural Networks", Human Factors, Vol.45,Winter 2003.

[5] Christos A. Frantzidis, Charalampos Bratsas, "Toward Emotion Aware Computing: An Integrated Approach Using Multichannel Neurophysiological Recordings and Affective Visual Stimuli", IEEE Transactions on Information Technology In Biomedicine, 2010.

[6] Arman Savran, Koray Ciftci, "Emotion Detection in the Loop from Brain Signals and Facial Images", University of Geneva, 2006.

[7] Bradley, M. M. & Lang, P. J., "The International Affective Picture System (IAPS) in the Study of Emotion and Attention", Handbook of Emotion Elicitation and Assessment, Oxford University Press, 2007.

[8] M.M. Bradley and P.J. Lang, "Measuring Emotion: The Self-Assessment Manikin and the Semantic Differential," J. Behavior Therapy Experimental Psychiatry, vol. 25, no. 1, pp. 49-59, Mar. 1994.

[9]Arnaud Delorme, "EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis", Journal of Neuroscience Methods 134, 2004.

[10] Naotoshi Seo, "Short Time Fourier Transform", IEEE International Conference on ICASSP, 2008.

[11] Abdul-Bary Rouf Suleiman, Toka Abdul-Hameed Fatehi, " Feature extraction techniques of EEG signal for BCI applications", Faculty of Computer and Information Engineering Department College of Electronics Engineering, University of Mosul, Iraq, 2007.

[12] Panagiotis C. Petrantonakis, "Emotion Recognition from Brain Signals Using Hybrid Adaptive Filtering and Higher Order Crossings Analysis", IEEE Transactions on affective computing, 2010.

[14] Mandeep Singh, Mooninder Singh and Surabhi Gangwar —Emotion Detection Using Electroencephalography (EEG):A Review , International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013 [in press].
[15] Mandeep Singh, Mooninder Singh and Surabhi Gangwar, —Feature Extraction from EEG for Emotion Classification, International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013[in press]
[16] Mandeep Singh, Mooninder Singh and Surabhi Gangwar —Arousal Detection Using EEG Signal, International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013 [in press].
[17] Omar AlZoubi, Rafael A. Calvo, "Classification of EEG for affect recognition: An adaptive approach", School of Electrical and Information Engineering,The University of Sydney, Australia, 2009.
[18] Mandeep Singh, Mooninder Singh and Nikhil Singhal — ANN Based Emotion Recognition Along Valence Axis Using EEG, International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013 [in press].
[19] Mandeep Singh, Mooninder Singh and Nikhil Singhal — Emotion Quantification Along Valence Axis Using EEG Signals, International Journal of Information Technology & Knowledge Management. Vol.7 no.1 Dec.2013 [in press].