International Journal of Bio-Science and Bio-Technology
Vol.7, No.3 (2015), pp.23-32
http://dx.doi.org/10.14257/ijbsbt.2015.7.3.03

EEG based Emotion Recognition from Human Brain using Hjorth Parameters and SVM

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Abstract

There are several methods of psychophysiological data collection from humans such as, Electrocardiogram (ECG), Galvanic Skin Response (GSR), Electromyography (EMG), and Electroencephalography (EEG). This paper is presenting the emotion recognition of EEG brain signals using Support Vector Machine (SVM). The emotions were elicited in the subjects using emotion related stimuli. We used the emotional stimuli from the International Affective Picture System (IAPS) database in this research. These stimuli belonged to five types of emotions in our experiment such as, happy, calm, neutral, sad and scared. The raw EEG brain signals were preprocessed to remove the artifacts. We introduced a feature extraction method using Hjorth parameters. The set of features were extracted from preprocessed EEG signals of each subject, separately. The combined feature set of all subjects was processed through SVM. The results had shown the 70 % accuracy of emotion recognition in arousal-valence domain over 30 subjects.

Keywords: *EEG, Emotion Recognition, HjorthParameters, Support Vector Machine.*

1. Introduction

Human computer interaction has become a part of everyday life. Similarly, emotions are important and constantly exist in a person's daily life. Emotions can provide many possibilities in enhancing the interaction with emotion-based computers, *e.g.*, affective interaction for autism or epilepsy patient. Emotion related research helps computer scientists in the development of emotion based HCI system. Many researchers had contributed successful research on emotion recognition such as speech, text, facial expressions or gestures as stimuli [1-14].

Emotion related expression is ubiquitous in the daily routine. It is an important factor in human interaction and communication. Although emotion is naturally aroused and felt by everyone, it is difficult to define. Previous research indicated the use of human brain signals. They suggested the recognition of internal brain emotion of subjects through brain signal patterns. However, there is no clear verdict on the role of the brain. Brain activity can be changed with people in a particular environment. Therefore, in order to find out the conclusion to satisfy the special need, some researchers are working analyzing human emotion under different types of emotional stimuli. Many scientists designed various experiments to retrieve emotion-related information from EEG signals with the advanced biomedical signal processing technology and analyzed data to look for the contact with emotion[15-24].

Emotion could be developed through "inner" thinking process by referring to the brain from the human senses (for example; visual, audio, tactile, odor, and taste). Many application areas (medical applications, EEG-based games, and marketing study) used the algorithms of "inner" emotion detection from EEG signals [12]. EEG based emotion

ISSN: 2233-7849 IJBSBT
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research is a challenging field within the area of biomedical signal processing, and several studies were performed to understand human emotion. Haiyan Xu *et al*. [14] investigated a variety of techniques for feature extraction and classification to recognize affective states from EEG signals. EEG signals were acquired in three different affective states and two pattern recognition methods have been tested: k-Nearest Neighbor (KNN), Linear Discriminant Analysis (LDA). Recognition rates of above 90% were achieved by using Higher Order Crossing (HOC) features with KNN classifier using all 54 channels. By applying channel reduction, recognition results of 89.3% were achieved using HOC features and KNN classifier. Khairuddin *et al.* [25] provide an application of time series analysis on EEG data in adults while playing the video game in 2D and 3D modes. They had compared the signal regularity with respect to viewing conditions (i.e., 2D, 3D active and 3D passive) by evaluating Hjorth complexity and CPEI parameters. Their results showed that the use of Hjorth complexity parameter as well as the CPEI showed a good indication that these two methods may be useful in quantifying the EEG activity during 2D and 3D visualization. Ahmad *et al*. [10] presented the emotion recognition method using SVM with accuracy of 56% over 15 subjects. Previous EEG study [8] generally investigated only two or three emotional responses from brain signals, such as when the person is happy ('positively excited'), or frustrated ('negatively excited'), or bored ('calm'). Khairuddin *et al*. showed the results of EEG signal regularity while playing the 2D and 3D games. Ahmad *et al*. had shown the method for classification of negative or positive valence/arousal emotions. SVM seemed to be the most common classifier has been employed in previous researches[21, 26].

The main goal of our research is to introduce the Hjorth Parameters [27] for feature selection. Furthermore, these features were used as input to Support Vector Machine (SVM) [28]. We focused on recognition of emotions from Electroencephalogram (EEG) signals. EEG signal features were selected under five brain regions on five different types of emotional stimulus. The EEG electrodes are divided into five brain regions, grouped as frontal (Fp1, Fp2, F3, F4, F7, F8 and Fz), central (C3, C4 and CZ); temporal (T7, and T8), parietal (P3, P4, P7, and P8), and occipital (O1 and O2). We also categorized the emotional stimuli into five emotions such as, happy, calm, neutral, sad, and scared. The remainder of the paper is structured as follows: Materials and Methods of our research will be described in Section 2. Section 3 includes the result and discussion. Finally, the conclusion will be presented in Section 4.

2. Materials and Methods

Thirty healthy males in the age group of 23 to 25 years old were recruited as normal subjects in this experiment. The subjects were given a simple instruction about the research work and stages of this experiment. EEG signals were collected using the 10/20 internationally recognized placement system. The EEG signals were recorded through Brain-Vision System (BrainProducts, Germany). We had used 18 electrodes (Fp1, Fp2, F3, F4, Fz, F7, F8, C3, C4, Cz, T7, T8, P3, P4, P7, P8, O1, and O2) which were inserted to record EEG signals using the Easy Cap.The reference channel was inserted in the occipital region of brain under the head back bulge point. The placement of EEG channels is displayed in the following Figure 1.

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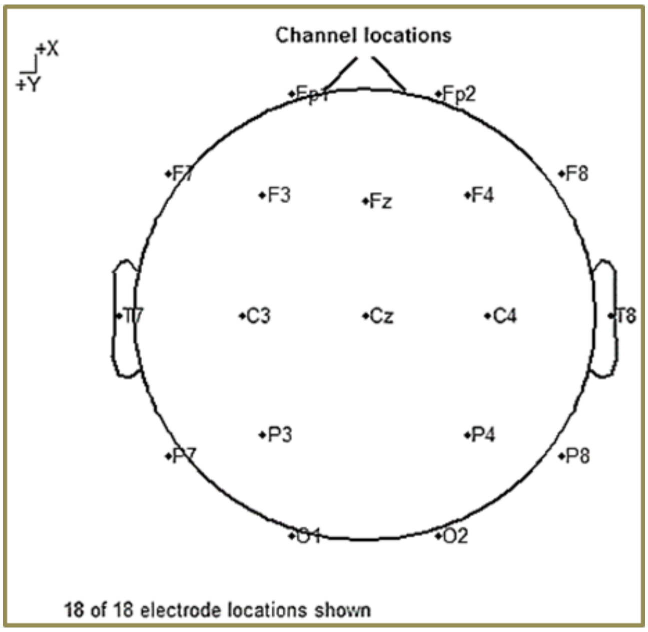

Figure 1. 10/20 Electrodes Placement

We adopted a method that is commonly used to evoke the different emotions from subjects by presenting the emotional stimulus with corresponding content [29]. The whole experiment was designed to produce emotion within the valence-arousal space. The following Figure 2 shows the 2D arousal-valence model with five affective emotional states. These two dimensions in Figure 2 are a subset of the 3D representation [19, 30] for collecting affective ratings through the IAPS. We defined the five affective states as sad, scared, happy, calm and neutral. On the basis of these ratings, 35 pictures (7 pictures x 5 states) were selected from uniformly distributed clusters along the valence and arousal axes. The emotional stimuli were selected from IAPS database. The Figure 3 displays the IAPS pictures arousal-valence level through the scatter plot chart. The selection of stimuli in this experiment is presented in Figure 3 with red circles for each emotional state.

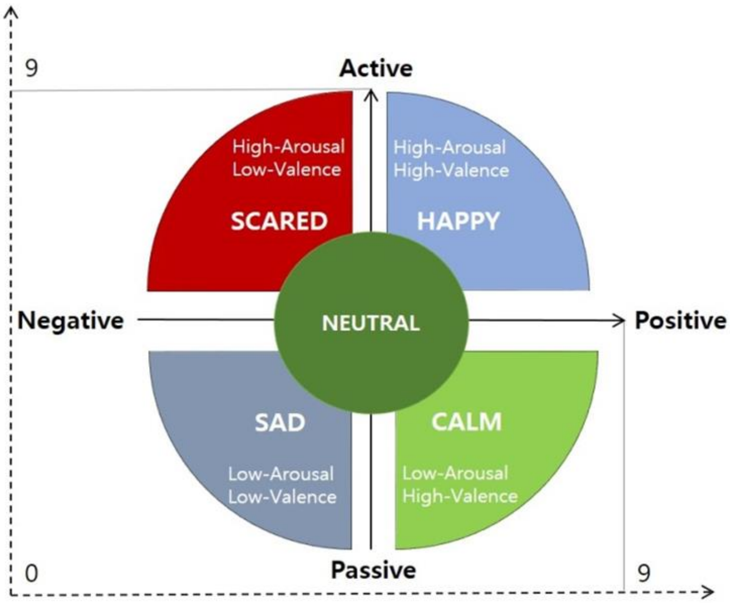

Figure 2. Arousal-Valence Model of Emotions

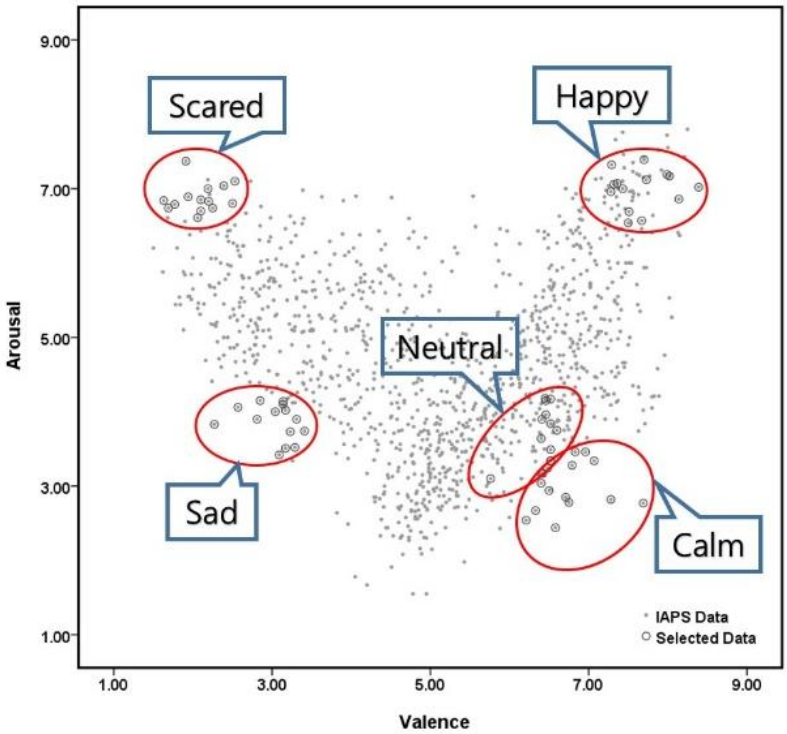

Figure 3. StimuliSelection from IAPS Database

The selected pictures were presented randomly for four seconds following another four seconds for resetting emotion with a blurred image. Due to its unknown emotional status before the projection of the first picture and after the projection of the last picture, a fixation mark (cross) was projected for eight seconds in the middle of the screen to attract the sight of the subject. Figure 4 shows the timing diagram of this experiment, where the total time of collecting EEG recording in this experiment was 296 seconds for each subject.

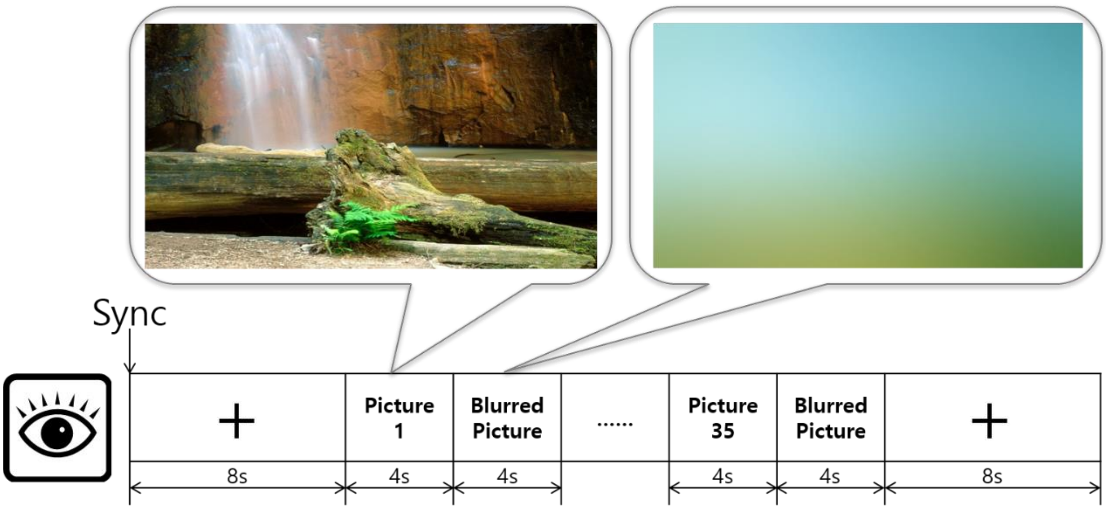

Figure 4. Stimulus Timing Diagram

Here, we presented the EEG brain signals with artifacts in Figure 5 (a). The eye blink is prominent in the frontal channels (Fp1 and Fp2) of the following EEG signals chart and

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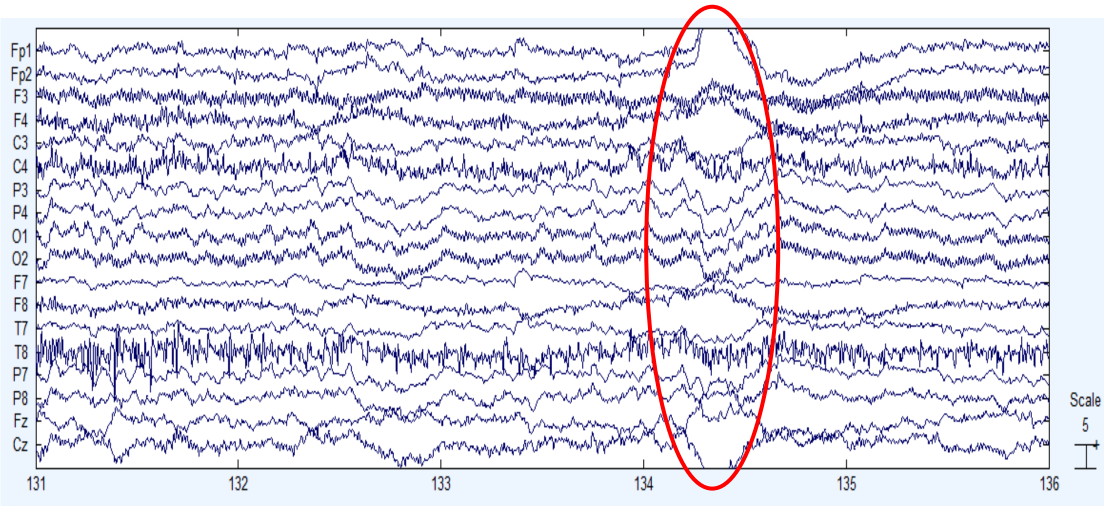
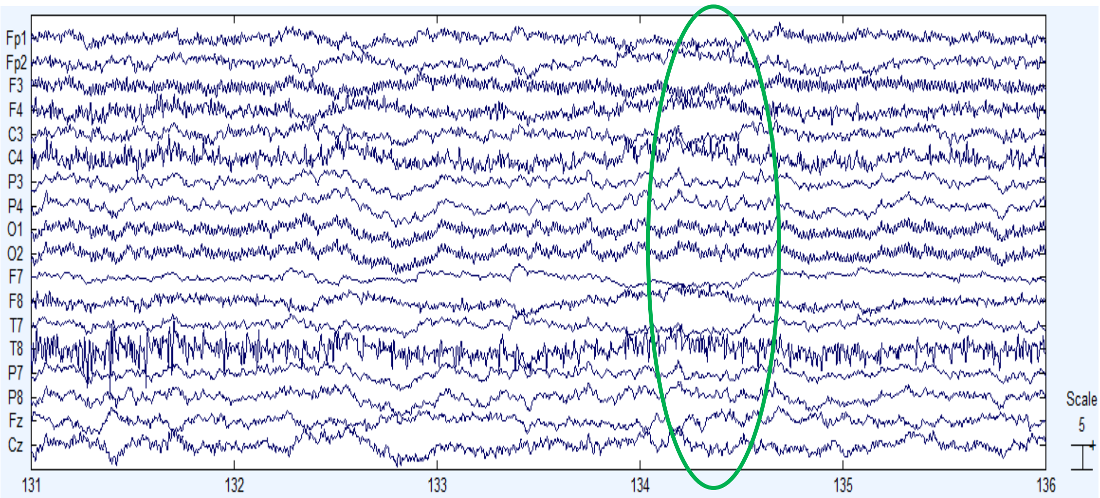
it is highlighted with a red oval. The raw EEG data were further processed through artifact rejection [31], filtering [32], and epoch selection. We had used the EEGLAB Toolbox in MATLAB for signals preprocessing.The cleaned EEG brain signals were retrieved after the artifact rejection. These signals are presented in Figure 5 (b) without any artifact in Fp1 and Fp2 and it is highlighted with green oval shape.



(a) EEG Brain Signals with Artifact



(b) EEG Brain Signals after Artifact Rejection

Figure 5. EEG Signals Artifact Rejection

The processed EEG signals were used to compute the Hjorth Parameters in time-frequency domain. Hjorth Parameters are based on statistical calculations, which were used to describe the characteristics of EEG signal in time domain. Hjorth Parameters are also known as normalized slope descriptors (NSDs) that include activity, mobility and complexity [33].

The processed data is further used for feature selection. Three Hjorth Parameters were usedforfeature selection from the selected frequency wave and brain lobe. We selected atotal of 75 features for each emotion class to input the classifier. These features consisted of three Hjorth Parameter at five frequency bands and five brain lobes. Five frequency bands (n) were considered within the frequency range of 0.5-50 Hz. We selected the 5

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frequency filters(nF2 = [0.5 4] [4 8] [8 13] [13 30] [30 50]) and each filter contains 2 points, which are low and high filter point. The second variable of feature selection arethebrain lobes which are five in total. These brain lobes were presented as frontal, central, temporal, parietal and occipital. The duration of extracted window is first 1000 milliseconds of every epoch. All EEG signal patterns were obtained at ith frequency filter and jth brain lobe and kth epoch.

$$[F^{75}]_k = \mathrm{Emo}\left(Fr_i, B_j, E_k\right) \tag{1}$$

Where, 'i', 'j' and 'k' are indices for frequency band, brain lobes and epoch, respectively. The function 'Emo' extracts the desired features at ith frequency band and jth brain lobe for every kth epoch. Further, these features are prepared for WEKA [34] to process the features dataset into SVM.

Features dataset were classified using SVM that is available in WEKA. During the classification, the classifier was trained to classify four groups of emotions separately. The techniques used had all the default parameter values as implemented in WEKA and ten-fold cross validation were used in all of our experiments.

3. Results and Discussion

The results from classifying the EEG data for all 30 subjects are presented in Figure6. The highest accuracy was obtained with SVM (70%) and presented on the y-axis. Figure6 presented the emotion groups on the x-axis. These groups are E5, E4, E3 and E2 consist of five emotions (happy, calm, neutral, sad and scared), four emotions (happy, calm, sad and scared), three emotions (happy, neutral, sad) and two emotions (happy, sad), respectively. The resultsarenotvery promising, indicating that there can still be noise in the processed data, or that the selected features are not representative for all subjects, which can be a problem.

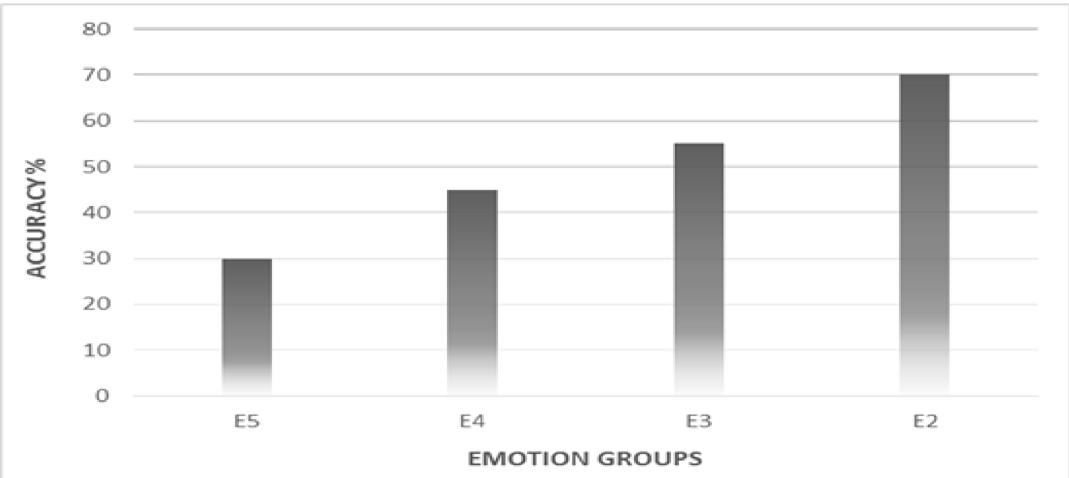

Figure 6. SVM Emotion Groups vs. Accuracy

The previous research [10]presented the results with an accuracy of 56% over 15 subjects. They tried different classification methods for the recognition of emotions in arousal-valence domain. Similarly, we adopted the SVM as a classifier for emotion recognition. We presented our results with better accuracy of two emotions (happy and sad) in arousal-valence domain that is 70% over 30 subjects.

The main purpose of our experiments was to evaluate our selected feature selction method through SVM. From our results, we can conclude that it is not trivial to process and classify data to be accurate over a high number of emotions.

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The classification result of all emotions was about 30% but we can see the improvement in accuracy over reduction of size in emotional group and classification accuracy of 70% is getting better up to two emotions.

4. Conclusion

We proposed a novel EEG feature extraction method for emotional stimuli (i.e., Happy, Calm, Neutral, Sad and Scared). In this paper, we employed the Hjorth parameters for our feature extraction method since it can efficiently represent event related properties of EEG signals. Our proposed method extracts the features from EEG signal through the band-pass filtering and combination of EEG channels (brain lobes). These features were extracted after applying the Hjorth parameters. Furthermore, these feature sets were passed to SVM for emotion classification.As previous research have discussed, the feature selection is a key challenge in effective computing. That's why the accuracy in our experiments greatly increased in the small group of emotions. It is difficult to find features that are generally working perfectly over a large number of subjects. Noise in EEG data is another possibility of low accuracy over more emotions. IAPS emotional stimuli might not be inducing strong enough emotion related perception on some subjects, which cause difficulty in classifying some emotions. We would be interested to explore more features withdifferent combinations to see how it affects the accuracy over many emotions. It would also be recommended to examine the results overa larger number of subjects in the future experiment.

Acknowledgements

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (MEST) (No. 2012R1A2A2A03).

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