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Towards emotion recognition of EEG brain signals using Hjorth parameters and SVM

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Abstract. There are several techniques of Psychophysiology data collation from human subjects. But, we focused in this paper to present the emotion detection of EEG brain signals using a classifier which is known as Support Vector Machine (SVM). The emotions were elicited in the subjects through the presentation of emotional stimuli. These stimuli were extracted from International Affective Picture System (IAPS) database. We used five different types of emotional stimuli in our experiment such as, happy, calm, neutral, sad and scared. The raw EEG data were preprocessed to remove artifacts and a number of features were selected as input to the classifiers. The results showed that it is difficult to train a classifier to be accurate over the high number of emotions (5 emotions) but SVM with proposed features were reasonably accurate over smaller emotion group (2 emotions) identifying the emotional states with an accuracy up to 70%.

Keywords: EEG, Emotion Stimulus, Hjorth, Support Vector Machine.

1 Introduction

Human computer interaction became a part of everyday life. Similarly, emotions are important and constantly exist in human's daily life. Emotion 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 to computer's scientist in the development of emotion based HCI system. Many researchers had contributed successful researches on emotion recognition such as speech, text, facial expressions or gestures as stimuli [1]. 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 [2]. Ahmad et al. [3] presented the emotion recognition method using SVM with an accuracy of 56% over 15 subjects. Previous EEG study [8] generally investigated the method for classification of negative or positive valence/arousal emotions.

The main goal of our research is to introduce the Hjorth Parameters [4] for feature selection. Further, these features were used as input to SVM [5]. We focused on

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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. The subjects were given a simple instruction about the research work and stages of this experiment. Further, EEG signals were collected using the 10/20 internationally recognized placement system. The EEG signals were recorded through the Brain - Vision System (Brain Products, 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) on the scalp to record EEG signals using the Easy Cap. We adopted a method that is commonly used to evoke the different emotions from subjects by presenting the emotional stimulus with corresponding content [6]. The whole experiment was designed to produce emotion within the valence-arousal space [7]. We defined the five affective states as sad, scared, happy, calm and neutral. On the basis of these ratings, 35 pictures (7 pictures × 5 states) were selected from uniformly distributed clusters along the valence and arousal axes. The selected pictures were presented randomly for four seconds following another four seconds for resetting emotion with a blurred image. The fixation mark (cross) was projected for eight seconds in the middle of the screen to attract the sight of the subject. Fig. 1 shows the timing diagram of this experiment, where the total time of collecting EEG recording in this experiment was 296 seconds for each subject.

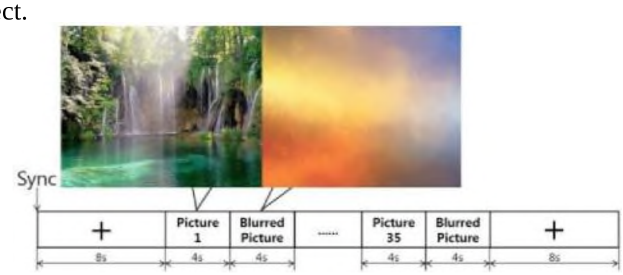

Fig. 1. Stimulus timing diagram

The raw EEG data were preprocessed through artifact rejection [8], filtering [9], and epoch selection. We had used the EEGLAB Toolbox in MATLAB. The processed EEG signals were used to compute the Hjorth Parameters in the time - frequency domain. Hjorth Parameters are based on statistical calculations which used to describe the characteristics of EEG signal in time domain. Hjorth Parameters are also known as normalized slope descriptors (NSDs) include activity, mobility and complexity [10]. The processed data are further used for feature selection. Three Hjorth Parameters were used for feature selection from selected frequency wave and brain lobe. We selected the total of 75 features for each emotion class to input the classifier. These features were consisted on 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 frequency filters ($_nF_2$ = {[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 variant of feature selection is brain lobes, which are five in total. These brain lobes were presented as frontal, central, temporal, parietal and occipital. The duration of extracting window is first 1000 milliseconds of every epoch. All EEG signal patterns were obtained at i^{th} frequency filter and j^{th} brain lobe and k_{th} epoch.

$$[F^{75}]k = Emo(Fri, Bj, Ek) \qquad (1)$$

where ‘i’, ‘j’ and ‘k’ are indices for the frequency band, brain lobes and epoch, respectively. The function ‘Emo’ extracts the desired features at i^{th} frequency band and j^{th} brain lobe for every k^{th} epoch. Further, these features prepare for WEKA [11] to process the feature dataset into SVM with ten-fold cross validation.

3 Results and Discussion

The classification results for all 30 subjects are presented in Fig. 2. The highest accuracy was obtained with SVM (70%) and presented on the y-axis. Fig. 2 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.

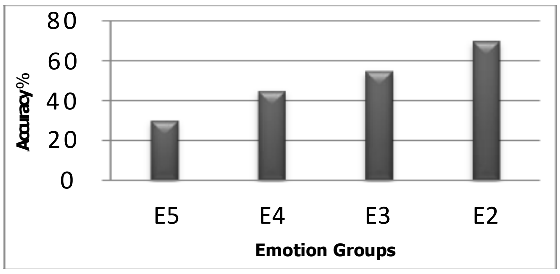

Fig. 2. SVM emotion groups vs. accuracy

The main purpose of our experiments was to evaluate our selected feature selection method through SVM. From our results we can conclude that it is not trivial to process and classify data to be accurate over the high number of emotions. 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. Band-pass filtering and combination of several EEG channels into specific brain lobes extracted the significant features for the SVM. As previous researches discussed the feature selection is a key challenge in affective computing. That’s why the accuracy in our experiments greatly increased on the small group of emotions. We would be interested to explore more features and different combinations of them to see how it affects the accuracy over many emotions. It would also be motivated to examine the results over more number of subjects in the future experiment.

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