EMOTION CLASSIFICATION OF EEG BRAIN SIGNAL USING SVM AND KNN

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ABSTRACT

Affective computing research field is growing in large scale with the frequent development of human-computer applications. These applications use information of mental or affective conditions of desired subjects to train their brain responses. Facial impressions, text physiology, vocal and other information about the subjects are used in the classification algorithms. However, the classification frameworks for EEG brain signals have been used infrequently due to the lack of a complete theoretical framework. Therefore, we present here an analysis of two different classification methods which are SVM and KNN. Four different types of emotional stimulus were presented to each subject. After preprocessing of raw EEG data, we employed Hjorth parameters for feature extraction of all EEG channels at each epoch. Five male subjects were selected in this experiment. Our results show that the emotion recognition from EEG brain signals might be possible.

Index Terms— *EEG, emotion, Hjorth, SVM, KNN*

1. INTRODUCTION

Nowadays brain signal processing technologies are opening the windows to new ways of looking at emotions and other affective states. Categorical and dimensional models have been debated since long time in the area of psychology. Formerly, a discrete number of emotions (e.g. 'Excited') can be detected or recognized through behavioral changes such as, physiological measures or facial actions [1, 2]. But, further assumes an essential set of variables considered to be two that are arousal and valence. Valence is described as going from very positive feelings to very negative and arousal also called activation, which is going from sleep to excited.

Chanel et al. [3] performed EEG based emotion classification with two emotional classes at arousal level. They used 64 electrodes at 1024 Hz for EEG recording. The authors presented the results of two classifiers such as, Fisher Discriminant Analysis (FDA) and NaiveBayes classifier with an accuracy of 70% and 72%, respectively. Khalili et al. [4] explored the physiological signals through EEG recording at arousal and valence levels. The authors performed the recognition analysis for three emotional classes. Their results showed the accuracy of Linear Discriminant Analysis (LDA) and K-Nearest Neighbor (KNN) were 40% and 61%, respectively. Horlings et al [5] used Encephalogram (EEG) for classifying five different kinds of emotion on two affective dimensions (valence and arousal, separately). They had used the training dataset from the database of the Enterface project [6], and extended it with their own data. They employed ten subjects for the task of EEG acquisition using a Truescan32 system. Emotion elicitation was achieved by using the International Affective Picture System (IAPS) protocol [7, 8]. Subjects were instructed to rate their level of emotion on a 2D arousal and valence scale according to the Self-Assessment Manikin (SAM) [9]. They accomplished two recording sessions consisted of 25 to 35 trials each. Rest time of 5 minutes was included in between of each session. Five pictures were presented on each trial, and each picture was shown for two and a half seconds. The EEG data was further preprocessed and filtered between 2-30 Hz. They adopted the band pass filtering to remove the artifacts and noise from the EEG signal. They also removed the baseline value from each EEG signal. They extracted about 114 features such as, frequency band power, cross-correlation between EEG band-power, peak frequency in alpha band and Hjorth parameters. They selected the best 40 features for each of the valence and arousal dimensions by using the max relevance min redundancy (mRMR) algorithm [10]. They used two classifiers to train the feature dataset. A separate classifier was selected for each dimension (arousal and valence). According to author's results, accuracy of 32% for the valence and 37% for the arousal dimension were achieved through SVM classifier with 3-fold cross validation.

Previous researches had commonly employed the KNN and SVM as a classifier of human brain signals. Both classifiers showed a good indication for further analysis in our research. The aim of our study is to classify four emotions in two dimensions of arousal and valence. We employed the SVM [11] and KNN [12] classifiers for recognition of emotion. Hjorth Parameters were selected as a feature extraction method. This study provides new data on EEG based emotion recognition, and presents a performance comparison of KNN and SVM using an adaptive classification technique. Section 2 discusses the material and methods used in this research work. Section 3 presents the results and discussion part of our paper, and Section 4 presents our conclusions.

2. MATERIALS AND METHODS

Our experiment was aimed to elicit the emotional response from subjects while they were watching the emotional stimulus. IAPS database was used during presentation of the emotional stimulus. This database was specifically designed for emotion based experiments in two dimensional domain of arousal and valence. We employed a common method to induce the distinct emotions from subjects by displaying the emotion-related stimuli [13-16]. We defined the four emotional states such as, happy, calm, sad and scared separately. On the basis of these ratings, 180 stimuli (45 stimulus $\times$ 4 states) were selected from equally distributed groups along the arousal-valence axes from IAPS database. The emotional pictures were selected with help of arousal/valence ratings from IAPS database. The picture rating is displayed in the Fig. 1 and our selection of emotional stimuli is shown with red circles.

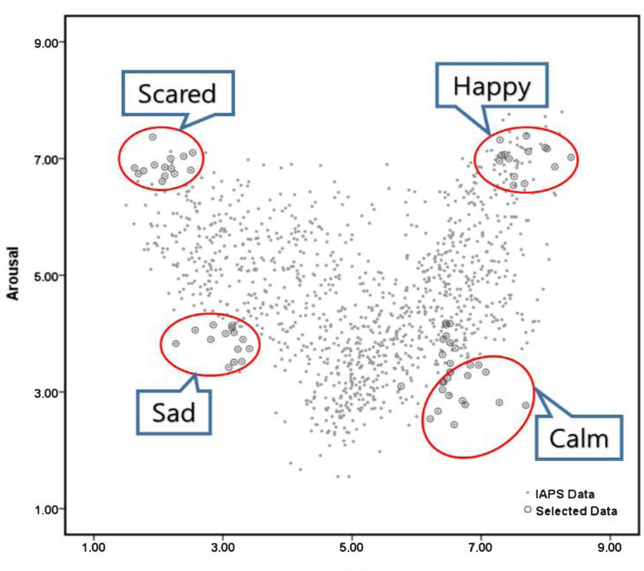


Fig. 1. The scatter plot of International Affective Picture System (IAPS) images database, based on valence-arousal model.

The EEG signal data were recorded through Emotiv-EPOC headset. Emotiv EPOC consists of 14 EEG channels plus 2 reference channels offering optimal positioning for accurate spatial resolution. This device used the international 10/20 electrode location system for electrode placement. The following Fig. 2 shows the EEG channel placement in our experiment.

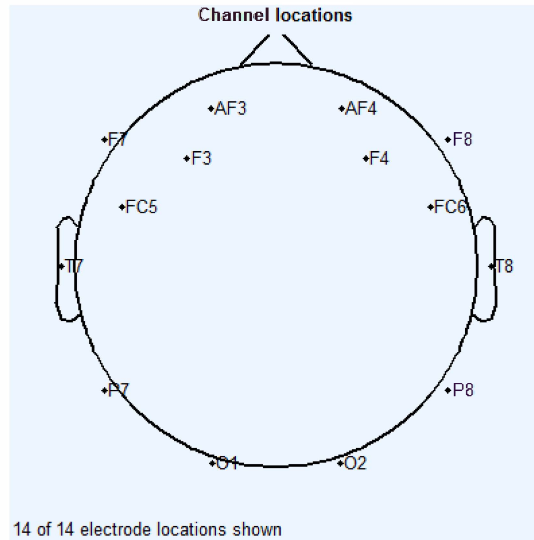


Fig. 2. Emotiv-EPOC headset 14 channel placement

We used 14 electrodes for recoding our experiment such as, AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, with CMS/DRL references in the P3/P4 locations. Emotiv EPOC uses a sequential sampling method at a rate of 128 samples per seconds (SPS).

In this paper, we are presenting the results of five male subjects those were participated in this experiment. All subjects were students of the same institute, and aged from 12 to 14 years. The selected subjects were middle school students of the same institution. They were informed about the purpose of our experiment. All subjects were given a simple presentation about the stages of experiment. They also signed the consent forms after the introduction of our experiment.

The stimulus was presented randomly for 1.5 seconds following another 0.5 seconds with a blank image which is black. A blank image was used to release the emotional feeling of a subject which was generated from previous stimulus. We used a fixation cross-sign that was projected for four seconds exactly in center of screen to attract the attention of the subject. Fig. 3 shows the timing diagram of this experiment where the total time of collecting EEG recording was 368 seconds for each subject.

The recorded EEG brain signals were preprocessed using the EEGLAB toolbox from SCCN Lab [17]. The toolbox is running under the Matlab. We cleaned the EEG signal data of each subject using Independent Component Analysis (ICA) and manual rejection of artifacts such as, eye blink, eye movement, muscle movement, and bad channel. We presented the raw signal of one subject in Fig. 4 (a). We can see the some noise artifacts in red oval which were produced during the recording session. We applied our method of artifact rejection. Fig. 4 (b) presents the clean EEG signal in a green oval after the preprocessing of raw data.

Hjorth parameters are statistical methods available in time and frequency domain [18]. These parameters compute the characteristics of EEG signal and they can be used as features for emotion classification [19]. The Hjorth parameters are defined as normalized slope descriptors (NSDs) which contain an activity, mobility and complexity. Hjorth parameters are derived by means of 1st and 2nd derivatives. The computational cost of these parameters is comparatively very lower than other methods.

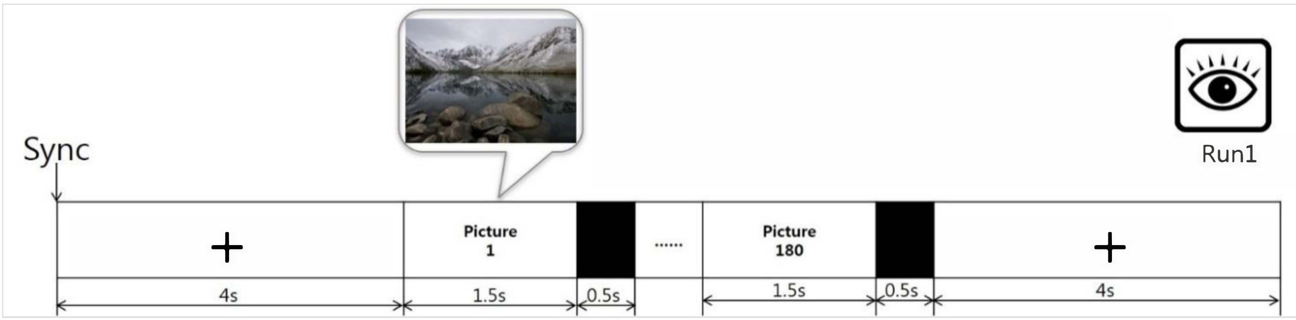
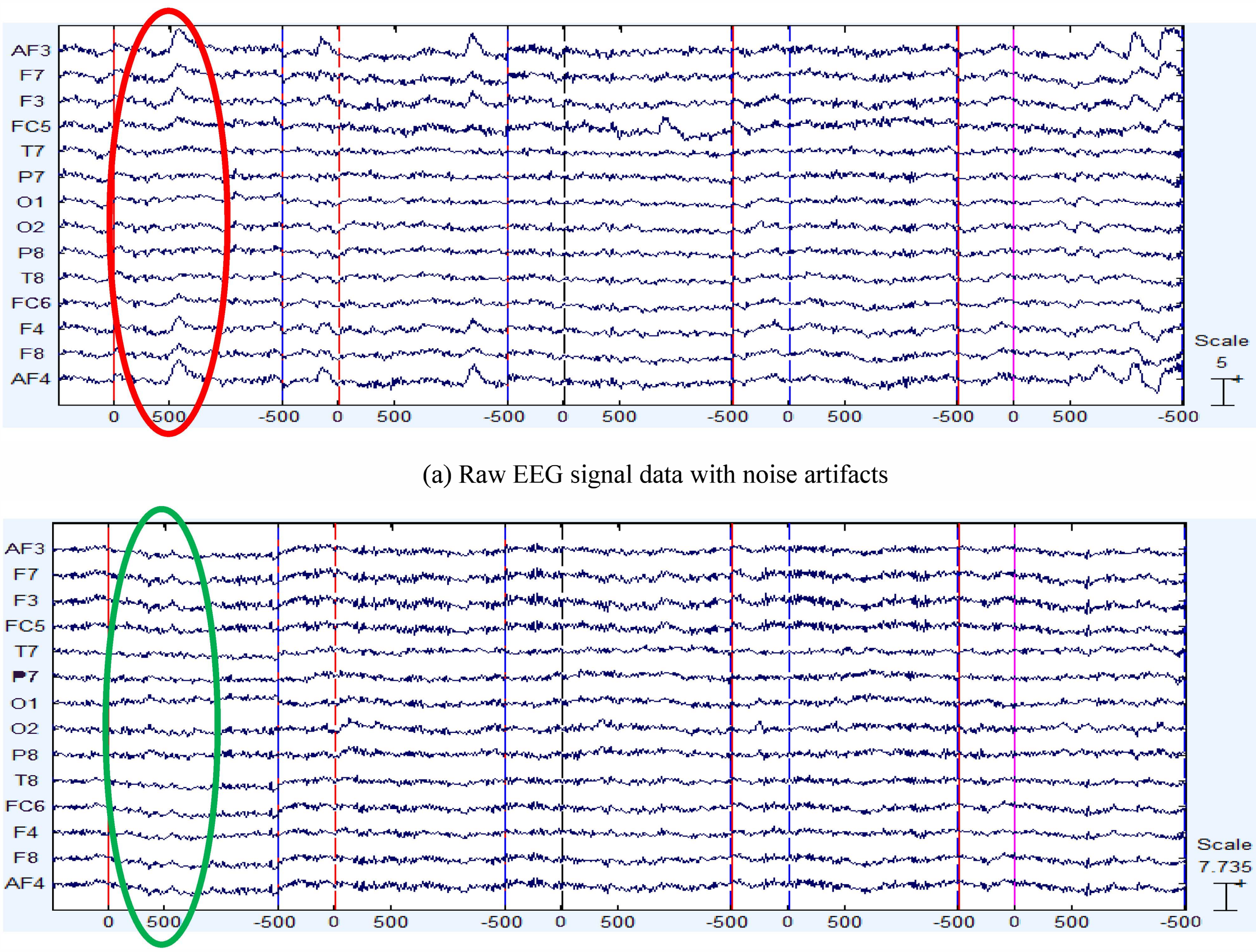


Fig. 3. Timing diagram of emotional stimuli



(a) Raw EEG signal data with noise artifacts

(b) Cleaned EEG signal data after preprocessing

Fig. 4. EEG signal preprocessing

We used a total number of 42 features set in our proposed method. Further, the extracted features set for each emotional class provided to the classifier. These features were consisted of three Hjorth Parameter and 14 EEG channels. We considered only single frequency range in proposed method which is 0.5-30 Hz. The duration of extracted window is first 1500 milliseconds of each epoch. All EEG signal patterns were obtained at i^{th} EEG channel and j^{th} epoch.

$$[I^{42}]_j = F_{hp}\left(EEG_i, E_j\right) \qquad (1)$$

where 'i' and 'j' are indices for EEG channels and epoch, respectively. The function 'F_{hp}' computes the total of 42 features set by using of Hjorth parameters at i^{th} EEG channel for every j^{th} epoch. This function returns the '$[I^{42}]_j$' as instance of 'j' epoch and it contains three parameter (*Activity, Mobility, and Complexity*) values against each EEG channel. Furthermore, these features were prepared for WEKA [20] to process the features dataset '$[I^{42}]_j$' into SVM. Each instance $[I]_j$ contains an epoch type as a class value for the classifier. We adopted a WEKA for classification analysis of extracted features dataset. The classifier was trained to recognize four different emotions in arousal-valence domain. We employed the default parameters of SVM which are available in WEKA. 10-fold cross validation was used for classification purpose in this analysis. Classification accuracy is presented in the following section.

3. RESULTS AND DISCUSSION

The classification results for five subjects are presented in Fig. 5. This figure contains the subjects on the x-axis while accuracy is displayed over y-axis. The two classifiers KNN and SVM can be identified by blue and green color bars, respectively. Both classifiers' results are displayed for each subject in same figure. The highest accuracy was obtained with KNN with k=3, which was 61%.

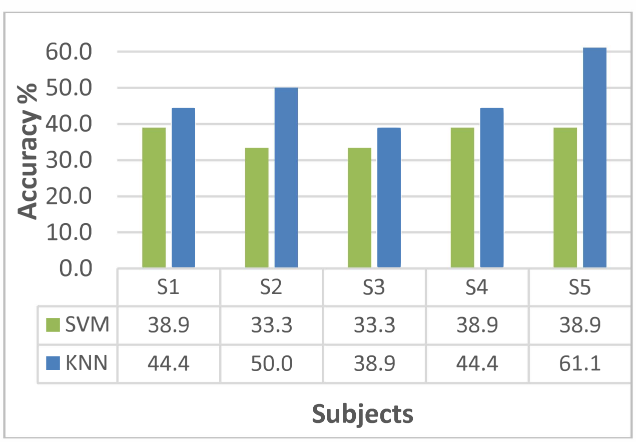


Fig. 5. SVM vs. KNN classification results

The main objective of our experiment was to evaluate our selected feature extraction method through SVM and KNN. Our result shows that it is not trivial to process and classify data to be accurate for every subject. Hence, the classification result of four emotions varies in subjects due to emotional dependency of subjects.

According to previous research work [5] that was already discussed in introduction of this paper, the SVM correctly classify affects in valence and arousal dimension with accuracy of 32% and 37%, respectively. Comparatively, our results shown that the accuracy of SVM is similar to previous research. But, we can conclude that the KNN is always better than SVM.

4. CONCLUSION

We proposed a novel method of emotion recognition from brain signals using 14 EEG channels. The results of our research show that the emotion recognition from brain EEG channels might be possible. Despite the lack of strong emotion related physiological indication to correlate the brain activity at the cortical level, our proposed method of feature extraction indicates the possibility of emotion recognition. However, this study mainly focused on the feature extraction and classification techniques that could be used for EEG signal processing. Our results have shown the high accuracy of KNN over SVM in all selected subjects. Future work would look at using a dynamic approach for recognizing the emotion in real time automated system.

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