Emotion Recognition Using the Emotiv EPOC Device

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Abstract. Emotion plays an important role in the interaction between humans as emotion is fundamental to human experience, influencing cognition, perception, learning communication, and even rational decision-making. Therefore, studying emotion is indispensable. This paper aims at finding the relationships between EEG signals and human emotions based on emotion recognition experiments that are conducted using the commercial Emotiv EPOC headset to record EEG signals while participants are watching emotional movies. Alpha, beta, delta and theta bands filtered from the recorded EEG signals are used to train and evaluate classifiers with different learning techniques including Support Vector Machine, k-Nearest Neighbour, Naïve Bayes and AdaBoost.M1. Our experimental results show that we can use the Emotiv headset for emotion recognition and that the AdaBoost.M1 technique and the theta band provide the highest recognition rates.

Keywords: EEG, Emotion recognition, Emotiv EPOC headset, AdaBoost.M1.

1 Introduction

Emotions play an essential role in many aspects of our daily lives, including decision marking, perception, learning, rational thinking and actions. Therefore, study of emotion recognition is indispensable.

The first approach to emotion recognition is based on text, speech, facial expression and gesture that were studied in the past few decades [1]. However, these methods are not reliable to detect emotion, especially when people want to conceal their feelings. Some emotions can occur without corresponding facial emotional expressions, emotional voice changes or body movements, especially when the emotion density is not very high. On the contrary, such displays could be faked easily. In order to overcome that disadvantage, the multi-modality approach has been introduced. A peripheral neurons system including heart rate variations, skin conductivity and respiration is a typical system for this approach [2, 3]. The advantage is that those modalities can hardly be deceived by voluntary control and are available all the time, without needing any further action of the users. Anttonen and Surakka found that heart rate decelerated in response to emotional stimulation, especially in response to negative stimuli compared to responses to positive and neutral stimuli [2]. Leng et al. verified that amusement produces a larger average and standard deviation of the heart rate

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than fear [3]. However, the user has to wear measurement devices which are hard to use and very expensive, and the emotion classification results are not high.

In recent years, researchers have attempted to develop hardware and software systems that can capture emotions automatically. This approach is called affective computing. One of those systems employs electroencephalography (EEG) signals recorded when users perform some brain activities. The advantages of this approach include 1) Brain activities have direct information about emotion, 2) EEG signals can be measured at any moment and are not dependent on other activities of the user such as speaking or generating a facial expression, and 3) Different recognition techniques can be used.

It has been found in the literature that the Naïve Bayes technique provides recognition accuracy of 70% for two classes [4]. Petrantonakis and Hadjileontiadis [5] studied changes in the EEG signal of subjects when presented with images of faces expressing six basic emotions. They showed that a recognition accuracy of 83% could be achieved using features based on higher-order crossings and support vector machine (SVM). Lin et al [6] extracted power spectrum density of different EEG sub-bands as features during different emotions induced during listening to music and a classification accuracy of 82% for four emotions was achieved. Using k-Nearest Neighbor (kNN) technique for two different sets of EEG channels (62 channels and 24 channels), Murugappan obtained an accuracy of 82.87% on 62 channels and 78.57% on 24 channels, respectively for five emotions [7].

Finding the frequency bands that most related to emotions is one of the main goals of emotion recognition. Li and Lu found that gamma band plays an important role in emotion recognition [9]. Dan Nie et al. suggested that higher frequency bands contributed to human emotional response rather than lower frequency bands [10].

In general there is no method based on EEG signals has been identified as the best [8]. Furthermore, it should be noted that once emotion recognition systems are more widely used in practice, new properties will have to be taken into consideration, such as the availability of large data sets or long term variability of the EEG signal. One difficulty encountered in such a study concerns the lack of published objective comparisons between classifiers. Ideally, classifiers should be tested within the same context, i.e., with the same users, using the same feature extraction method and the same protocol. Currently, this is a crucial problem for emotion recognition research [8].

On the other hand, providing reliable recommendation is the main task of recommender systems in e-commerce, entertainment and society research. For subjective and complexes products such as movies, music, news, user emotion plays surprising critical roles in the decision process. The use of EEG data to recognise user emotion will contribute to building reliable recommender systems.

In this paper, we present an automatic EEG-based emotion recognition system that can record the EEG signals from users and measure their emotions when they are watching movies. We propose to use the commercial Emotiv EPOC headset since it is significantly less expensive than other EEG devices. The EEG data are then filtered to get separate frequency bands to train emotion classifiers with the four well-known classification techniques that are SVMs, Naïve Bayes, kNN and AdaBoost.M1.

2 The Proposed EEG-Based Emotion Recognition System

The proposed emotion recognition system records EEG data using the Emotiv EPOC wireless headset [9]. This Emotiv headset has 14 electrodes locating at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4 following the American EEG Society Standard. The Emotiv EPOC headset does not require a moistened cap to improve conduction. The sampling rate is 128Hz, the bandwidth is 0.2-45Hz, and the digital notch filters are at 50Hz and 60Hz.

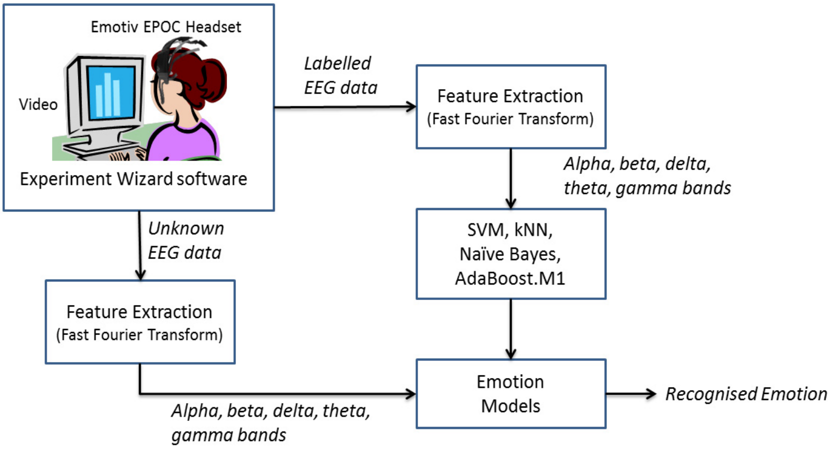

Fig. 1. The proposed EEG-based emotion recognition system

We used the Experiment Wizard software tool [10] for acquiring raw EEG data from the Emotiv headset while a participant is watching videos. This software is useful to design an experiment, to prepare and configure multimedia, and to collect the EEG data in a structured and systematic way.

The raw EEG data is found in the frequencies below 30Hz. There is not much brain activity with very low frequencies and artefact occurs at a lower frequency below 2Hz, therefore a 2-30 Hz band-pass filter was applied to separate the EEG data in to 4 bands that are 2-4Hz (delta), 4-7Hz (theta), 8-12Hz (alpha) and 12-30Hz (beta). Fast Fourier Transform (FFT) with 5s non-overlapping window was used to compute signal power in each of four frequency bands for each channel and the mean of each channel. The average EEG signal and the 4 frequency bands (alpha, beta, delta and theta) obtained from the 14 electrodes will provide up to 70 features (5×14) for the recorded EEG data.

In the training phase, the labelled EEG data, i.e. the data from a known emotion, are recorded and sent to the four well-known algorithms that are SVM, *k*NN, Naïve Bayes and AdaBoost.M1 to build a model for that emotion.

In the recognition phase, an unknown EEG data will be compared with the built emotion models and the recognised emotion is the label of the best matching model.

3 Data Acquisition

3.1 Subjects

The EEG data in our experiments were recorded from subjects aged around 30, who were healthy and right-handed. All the subjects were informed about the purpose of this experiment. None of them suffered at the time of experiment from a chronic disease, mental disorder, drugs or alcohol abuse, depression or anxiety, hearing defects or neurological disorder and none of them were on medication.

3.2 Stimuli

There are many different methods to induce emotion like films, music, pictures or imagination. In order to obtain affective EEG data, experiments were carried out with different kinds of stimuli as audio, visual, and combined ones to induce emotions. As stimuli, video clips are extracted from films (video and audio) taken from the Film-Stim database [11]. The emotional impact of the stimuli from the database has been scientifically assessed. The reason why we chose movies as stimuli is that audio-visual stimuli are highly benefit for arousing human emotion [12]. In a meta-analysis Westermann *et al.* found that film/story is the most effective method to induce positive and negative emotional states [13]. In our experiments, we were mainly concerned about sadness and happy emotions. Thus each of the movie clips was classified into these two kinds of emotions. The advantages of this approach are that there is no need for a professional actor and that responses should be closer to the ones observed in real life.

3.3 Procedure

A set of movie clips classified in to amusement and fear emotions was used. About 8 movie clips (4 video clips for each of the emotions) were randomly selected in each experiment and presented to a participant. The participant was alerted and was asked to focus on a movie clip during its presentation. There is a rest period of 2 minutes between two consecutive movie clips. We also recorded the EEG data when the participant was watching non-emotional movie clips and labelled this data set as neutral. In total, there were 3 classes which were amusement, fear and neutral for recognition.

3.4 Data Recordings

The Emotiv EPOC wireless headset was used in our experiments to record the EEG data. We used the Experiment Wizard software tool for acquiring the raw EEG data. The default EEG sampling rate from the Emotiv headset is 128Hz, which provides enough samples for the frequency ranges of the 4 frequency bands. The EEG data were also filtered to remove noise and artefacts. All of the EEG data from the 14 channels (electrodes) were used for band pass filtering and fast Fourier transform to extract up to 70 features as described in the previous section.

4 Experimental Results and Discussion

The four techniques SVM, *k*NN, Naïve Bayes and AdaBoost.M1 to build emotion models were obtained from WEKA [14]. The parameter *k* was set to 3 and Euclidean distance was used in the *k*NN technique. The linear kernel was selected for the SVM technique. For the AdaBoost.M1 technique, the kernel J48 was used. We chose those settings to obtain the highest performance for those techniques. In our experiments, the 5-fold cross validation was used to have recognition rates for the four techniques and the results are presented in Table 1. The highest recognition rate was achieved by the AdaBoost.M1 technique. The SVM technique performed better than the *k*NN and Naïve Bayes techniques.

Table 1. Emotion recognition rates for SVM, kNN, Naïve Bayes and AdaBoost.M1

	SVM	*kNN*	*Naïve Bayes*	*AdaBoost.M1*
Emotion recognition rate	89.25%	83.35%	66%	**92.8%**

We also investigated emotion recognition rates for each of the delta, theta, alpha and beta bands. Table 2 shows the emotion recognition rates for each of the 4 bands. The average recognition result for those bands is also presented. The last columns in Table 2 present the recognition rates for the non-filtered EEG data which include the data for the 4 above-mentioned bands and the data for gamma band.

The system performances for the alpha and beta bands are obviously better than those for the delta and theta bands. This result suggests that human emotional response is mainly related to high frequency bands rather than low bands. This finding is consistent with the studies of other researchers with a note that the frequency band that provides the highest performance is subject-dependent [12].

Table 2. Emotion recognition rates for the 4 frequency bands with AdaBoost.M1

	Delta	*Theta*	*Alpha*	*Beta*	*All*
Emotion recognition rate	69.95%	68.4%	75.5%	89.7%	92.8%

5 Conclusion

We have presented our emotion recognition system using the EEG data recorded when the participants were watching emotional movies to build emotion models with the four techniques Naïve Bayes, KNN SVM, and AdaBoost.M1. The recognition results have shown that the low-cost Emotiv EPOC headset is good for implementing emotion recognition applications for recommender systems in e-commerce, entertainment and society.

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