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EEG-Based Emotion Detection in Music Listening

R. Ramirez, S. Giraldo, Z. Vamvakousis
Department of Information and Communication Technologies, Universitat Pompeu Fabra

Correspondence: R. Ramirez, Department of Information and Communication Technologies, Universitat Pompeu Fabra, Roc Boronat 138, 08018 Barcelona, Spain. E-mail: rafael.ramirez@upf.edu

Abstract. The study of users' emotions in computer interaction has increased in recent years. In this paper we describe an approach to detect emotion from brain activity, recorded as electroencephalograph (EEG) with the Emotiv Epoc device, during music listening. After extracting features from the EEG signals we characterize the emotional state of a person by mapping their brain activity to a coordinate in the arousal-valence 2D emotion space. We then apply machine learning techniques to classify EEG signals into happy/sad and angry/tender emotional states. The obtained classifiers may be used to automatically tag or recommend music based on the listeners' EEG data

Keywords: EEG, Emotion Detection, Machine Learning, Music

1. Introduction

The study of users' emotions while interacting with multimedia computer systems has increased in recent years. This is due to the growing need for computer applications capable of detecting the emotional state of users and adapt accordingly [Picard and Klein, 2002]. Motivated by every day interaction among humans, the majority of the research in this area has explored facial and voice information as source of emotion cues. However, emotions are not always manifested by means of facial expressions and voice information. Facial and voice information is related only to behavioral expression which can be consciously controlled and modified, and which interpretation is often subjective. A still relatively new field of research in affective brain-computer interaction attempts to detect emotion using electroencephalograms (EEGs) [Chanel et al., 2006; Lin et al., 2010]. There have been several approaches to EEG-based emotion detection, but there is still little consensus about definite conclusions.

In this paper we describe an approach to decoding emotion from EEG data obtained with a (low-cost) Emotiv EPOC headset. Subjects are presented with music fragments previously annotated with particular emotions (i.e. happy, sad, angry, tender) while we record their response EEG activity. We characterize the emotional state of a person by mapping their EEG signals to a coordinate in the arousal-valence 2D emotion space (e.g. happiness is a state with high arousal and positive valence, whereas sadness is a state with low arousal and negative valence). We then apply machine learning techniques to classify EEG signals into happy/sad and angry/tender emotional states. Our approach differs from most previous works in that we do not rely in subject self-reported emotional states during stimuli presentation. Instead, we use a set of emotion-annotated music pieces from films soundtracks.

2. Material and Methods

2.1. Data Collection

EEG data in this study were collected from 4 healthy subjects (2 males and 2 females) with average age of 27.25 during listening to emotion-annotated 12–18 seconds music fragments. Data were collected using the low-cost Emotiv EPOC headset, recently released by the Emotiv Company. This headset consists of 14 data-collecting electrodes and 2 reference electrodes, located and labeled according to the international 10-20 system. Following the international standard, the available locations are: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. The EEG signals are transmitted wirelessly to a laptop computer. Subjects listened to selected film soundtrack fragments previously tagged according to their emotional content. Based on these annotations, we selected 8 music fragments covering all four quadrants in the arousal-valence emotion plane (2 in each quadrant).

Initially, the subjects are informed about the experiment procedure and instructed to follow the usual guidelines during stimuli presentation (e. g. do not move). Subjects were instructed to close their eyes and not to produce any facial movements during the experiment. Once this was done, the 8 music fragments are randomly presented each one for 12 seconds and a 10 second silent rest is inserted between stimuli. The purpose of the 10 second silent rests is to set a neutral emotional state of mind in between stimuli.

2.2. Feature Extraction

From the EEG signal of a person, we determine the level of arousal, i.e. how relaxed or excited the person is, by computing the ratio of the beta and alpha brainwaves as recorded by the EEG. We measure the EEG signal in four locations (i.e. electrodes) in the prefrontal cortex: AF3, AF4, F3 and F4.

In order to determine the valence level, i.e. negative or positive state of mind, we compare the activation levels of the two cortical hemispheres. Specifically, we estimate the valence value in a person by computing and comparing the alpha power a and beta power b in channels F3 and F4.

2.3. Learning Task

We approach this problem as a two 2-class machine learning classification problem - we apply a multi-layer perceptron with two hidden layers. In particular, we are interested in inducing two classifiers of the following forms:

$\text{Classifier}_1(\text{EEGdata}([t, t+c])) \rightarrow \{\text{happy}, \text{sad}\}$

$\text{Classifier}_2(\text{EEGdata}([t, t+c])) \rightarrow \{\text{angry}, \text{tender}\}$

where $\text{EEGdata}([t, t+c])$ is the EEG data observed at time interval $[t, t+c]$ and $\{\text{happy}, \text{sad}\}$ and $\{\text{angry}, \text{tender}\}$ are the sets of emotional states to be discriminated. The results reported in this paper are obtained with c=4s and with increments of t of 1 s. For each subject in the EEG data sets we train a separate classifier.

3. Results

The expected accuracy of a default classifier (one which chooses the most common class) for the same tasks we consider in this paper is 50 % (measured in correctly classified instances percentage). The average accuracies we obtain for the happy-versus-sad, and the angry-versus-tender classifiers using a multi-layer perceptron classifier are 86.33 %, and 77.27 %, respectively. We evaluated each induced classifier by performing 10-fold cross validation in which 10 % of the training set is held out in turn as test data while the remaining 90 % is used as training data. When performing the 10-fold cross validation, we leave out the same number of examples per class. In the data sets, the number of examples is the same for each class considered, thus by leaving out the same number of examples per class we maintain a balanced training set.

3.1. Discussion

The difference between the results obtained and the accuracy of a baseline classifier, i. e. a classifier guessing at random, confirms that the EEG data contains sufficient information to distinguish between happy/sad and angry/tender states, and that machine learning methods are capable of learning the EGG patterns that distinguish these states. It is worth noting that also investigated other algorithms (e. g. decision trees and k-NN) and all produced better than random classification accuracies. This supports our statement about the feasibility of training classifiers using the Emotiv Epoc for the tasks reported.

4. Conclusions

We have explored the use of machine learning techniques for the problem of classifying the music-induced emotional state of a person based on EEG data using the Emotiv Epoc headset. In particular, we presented results obtained with a multi-layer perceptron for discriminating between happy-versus-sad and angry-versus-tender states. Our results indicate that EEG data obtained with the Emotiv Epoc device contains sufficient information to train successful classifiers for these emotional states, using machine learning techniques. Furthermore, we proved that it is possible to train successful classifiers without self-assessment information about the emotional states by the subjects.

Acknowledgments

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