Emotion Detection using EPOC EEG device

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Abstract. With successful classification of emotions we could get instant feedback from users and increase the potential of affective computing. In our approach, we aim to evaluate EEG device Emotiv EPOC and classify emotions from the data captured by this device. We proposed a method of emotion classification, which we evaluated on an existing dataset. The preliminary results show 37.72% accuracy of our approach. In addition, we conducted an experiment, in which participants watched music videos. We used EPOC to capture the electrical signal from their brains. In order to verify the potential of the EPOC Emotiv device for classification of the emotions, we plan to compare it with one of the existing tools, namely Noldus FaceReader.

1 Introduction and related work

Due to the growing need for computer applications capable of detecting the emotional state of the users [9], studying emotions in informatics has increased. The direct options of detecting the emotions are inquiries and questionnaires with specific questions which participants answer on the Likert scale. The questions could be divided into categories based on their function in the questionnaire: description of the situation, description of the emotional reaction, control of emotion. The questionnaires are then evaluated and emotions are classified based on the answers [12]. Because of the fact that every participant has to answer all the questions and those need to be manually evaluated, it is not a very efficient method. That is the reason for inventing new methods for classifying emotions for example through physiological responses.

Motivated by every day interaction among humans, a great part of the research in this area has explored detecting emotions from facial and voice information. Under controlled situations, current emotion-detection computer systems based on such information are able to classify emotions with considerable accuracy [11]. One of the available software solutions is *Noldus FaceReader*[1], which can recognize six emotional states: joy, sadness, anger, surprise, fear, disgust, and a neutral state. These states can be analysed from live recording, existing video, or a picture [5]. However, it depends on good light conditions and the accuracy could be also decreased by an object covering part of a participant's face, e.g., glasses. In order to address these shortcomings, other approaches to detect emotions have been proposed which focus on different physiological information, such as heart rate, skin conductance, and pupil dilation [11].

A still relatively new field of research in affective brain-computer interaction attempts to detect emotions using electroencephalograms (EEGs) [3], [4]. While classifying emotions from EEG signals, many researchers focus on changes in activity of alpha and beta waves. Studies show that there is a relationship between the cognitive activity of the brain and a decrease of the activity in the

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[1] http://www.noldus.com/human-behavior-research/products/facereader

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alpha band [8]. Different approaches are used for emotion classification from the EEG signal. Choppin used neural networks to recognize one of six emotions with 64% accuracy [4]. Takahashi [11] used headband with three dry electrodes for classifying five emotions (joy, anger, sadness, fear, relaxation). He used several bio-signals (EEG, hearth beat, skin conductance) and achieved accuracy 41.7% with the use of SVM algorithm. Oude [2] described method for recognizing emotions from EEG signal by BraInquiry EEG PET device. He used limited amount of electrodes and a linear classifier based on the FDA algorithm. He determined combinations of positive/negative and strong/weak emotions. Lin et al. [7] used machine learning for categorizing EEG signal based on the questionnaires which participants answered after listening to the music. They tried to classify four emotional states: joy, anger, sadness, and excitement.

The most of the studies used EEG devices available only for research and also did not compare them to other approaches. We, on the other hand, classify emotions with the use of affordable EPOC Emotiv EEG device. In our work we try to classify six basic emotions – joy, sadness, anger, surprise, disgust, fear, and neutral emotion – from the raw EEG data. The goal of our work is to evaluate Emotiv EPOC, one of the first commercial and affordable EEG devices, in classifying concrete emotions. For this purpose, we conducted an experiment, in which we played music videos to our participants in order to elicit their emotional response, while we recorded the EEG signal. We use the collected data to classify emotions by using machine learning techniques and compare the results with another approach for detecting emotions, *Noldus FaceReader*, in order to see how these two approaches (EEG signal processing vs. face expression analysis) perform at same conditions. In the experiment we also created dataset which could be used for future works.

2 Method for emotion recognition

Our method is based on the method was used by the psychologists. In order to represent emotions we use dimensional approach [10] which is based on the fact that all subjective feelings could be projected into the 3D space where dimensions are: (*i*) *arousal* – positive/negative emotion, (*ii*) *valence* – strong/weak emotion, and (*iii*) *tension* – tensed/relieved emotion.

We omit the third dimension due to the difficulty of determining the amount of tension. When classifying emotions by this method, respondents identify how positive (valence) and how strong (arousal) was their emotion. These values are projected to 2D space, called Valence–Arousal model (see Figure 1), which could be divided to four quadrants: strong-negative emotions, strong-positive emotions, weak-negative emotions and weak-positive emotions. We try to compute valence and arousal from EEG signal and use them as one of the features for machine learning algorithm to recognize specific emotions.

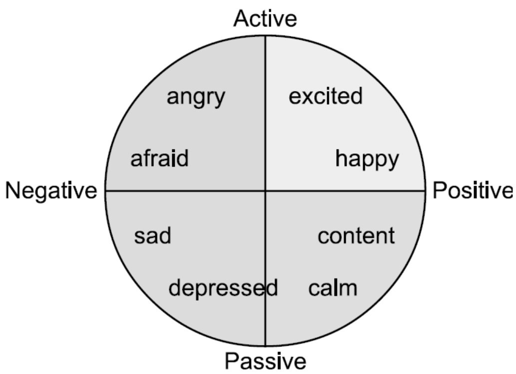

Figure 1. Valence-Arousal model [2].

2.1 Pre-processing

Before any classification we first pre-process the data. We apply DTW (Discrete wavelet Transform) on the raw EEG data. This algorithm divides signal to the specific bands and after we use DWT and inverse DWT several times with optimal parameters, it is possible to extract alpha and beta waves from the signal at the cost of less samples. Then we compute strength of those waves in individual stimuli with the following formula:

$$\mathrm{P} = \frac{1}{N} \sum_{k=0}^{N-1} x^2 \qquad (1)$$

where P is strength of the signal, N is a sample count in presented stimuli, and x is electric charge in microvolts.

2.2 Valence and arousal representation

High arousal is characterized by large amount of beta waves and low activity of alpha waves. Beta waves are associated with higher brain activity and alpha waves with relaxation. So beta/alpha ratio could be indication of the state of arousal the subject is in. The beta and alpha waves appear the most and are best measurable in the frontal and the middle part of the brain, so we take signal from electrodes in this area [1], [8]:

$$\mathrm{Arousal} = \beta\,(\mathrm{AF3} + \mathrm{AF4} + \mathrm{F3} + \mathrm{F4}) \,/\, \alpha\,(\mathrm{AF3} + \mathrm{AF4} + \mathrm{F3} + \mathrm{F4}) \qquad (2)$$

where α is a strength of alpha waves, β is a strength of beta waves, and AF3, AF4, etc. are data from the individual electrodes.

Based on the differences in the hemisphere activities it is possible to recognize if a respondent reacts on the stimuli negatively or positively. We use this fact to determine the amount of valence. By alpha/beta ratio we compute the inactivity of the brain, and by subtracting inactivity of the hemisphere we compute valence [1]:

$$\mathrm{Valence} = \alpha\,(\mathrm{F4}) / \beta\,(\mathrm{F4}) - \alpha\,(\mathrm{F3}) / \beta\,(\mathrm{F3}) \qquad (3)$$

2.3 Feature selection

Accuracy of our method depends on how we will map changes in the EEG signal to the features which we will use as an input for the machine learning algorithm. Even when formulas (2) a (3) were proven to work with a certain accuracy [1], we do not to rely solely on them, but use them as one of the features for the machine learning. We also use other features derived from the EEG data which could distinguish changes in the EEG signal – power of alpha and beta waves in the specific electrodes, and extreme and mean values in the raw data in the specific electrodes.

3 Evaluation

We try to recognize six different emotions – joy, sadness, anger, surprise, disgust, and fear. We tested our method on an existing dataset and then we conducted an experiment in User Experience and Interaction Research Centre at FIIT STU in Bratislava.

3.1 Preliminary evaluation on the dataset

We have access to the multimodal dataset[2] [6] for the analysis of human affective states which contains data from 32 participants who watched 40 one-minute long excerpts of music videos. To

[2] http://www.eecs.qmul.ac.uk/mmv/datasets/deap/index.html

every music video, participants assigned the amount of arousal and valence. The EEG data were recorded with 32 electrode EEG device. The dataset is not ideal for our research due to the missing information about specific emotions the respondents felt.

Dataset also contains data from online questionnaires which were used to choose the most emotional music videos for creating this dataset. The respondents chose the amount of valence, arousal, and 1 of the 16 emotions they were feeling. However, the EEG data were not recorded in this part of the experiment as it was conducted online.

In the ideal circumstances, we would have EEG data labelled by the specific emotion (this motivated us to create our own dataset). Nevertheless, we can test our method on this data and evaluate it partially.

3.1.1 Predicting valence and arousal with linear regression

Firstly, we applied linear regression in order to predict the valence and arousal from the EEG data. If the data were labelled with the specific emotion, we could skip this step and predict the emotions directly from the EEG data. In this case, we could not do this, since the dataset lacks this information, but we are able to at least see if it is possible to map the EEG data to the real feelings of the people.

We split the data into training and testing set, where testing set contained 30% of the data. The standard deviation of arousal and valence was the same, 0.068. We measured the accuracy of the trained model with the variance score, achieving variance score 0.995 on predicting arousal and 0.996 on predicting valence, which means that we could predict actual feelings from the EEG data with a sufficient accuracy.

3.1.2 Emotion classification with the support vector machines

Next, we used the data from the online questionnaires which contained arousal and valence, emotions selected by the respondents, but no EEG data. We tried to predict emotions from the arousal and valence values. Only those two features are not enough to predict emotions so we derived other features like maximum and minimum valence and arousal for every music video in order to increase accuracy of the algorithm.

We used support vector machines to classify six emotions: joy, surprise, sadness, fear, disgust, and anger. We were able to predict emotions with the 35.71% accuracy. The different emotions could be predicted with different accuracies. This could be due to the differences in the sample count for the individual emotions; so we decided to apply oversampling on the training set to make it more balanced. After this, the accuracy slightly increased to 37.72%.

Such accuracy is not sufficient; we tried to increase it by lowering the number of emotions which participants were be able to choose from in our own experiment. Thanks to that we should have more samples of the same emotions. In the experiment, we also collected information about emotions the participants felt while watching music videos.

3.2 User experiment with Emotiv EPOC

In order to evaluate our approach, we decided to replicate experiment carried out in [6], which resulted into the dataset that we used for the preliminary evaluation. In the experiment the participants watched music videos as in the original experiment, but our participants should also choose in the questionnaire what emotions they felt while watching the individual music videos.

3.2.1 Experiment setup

The participants in our experiment were supposed to watch 20 one minute music videos highlights, the most of which were also used in [6] and should mainly evoke one dominant emotion. Before every video, fixation cross was projected for 5 seconds and after each video participants answered questionnaire with 3 questions:

- How strong was the emotion that you felt? (arousal)

- How positive was the emotion that you felt? (valence)
- What emotion did you feel the most?

In the first two questions participants could answer on the scale 1-10 and for the last question these options were proposed: joy, sadness, anger, disgust, fear, surprise, and neutral emotion. We added "neutral emotion" option, because of the fact that some people could get less emotional while watching these music videos and we do not want to force them to choose the emotion as it could skew our data. Since participants answered questions in between the videos and before every video the fixation cross was projected, there should not be any impact of the previous video on their emotions.

For managing the experiment, we used Tobii Studio, where we played our videos and displayed the questionnaires. EEG data were recorded with the EPOC Emotiv device. We also recorded face of the participants using the camera and *Noldus FaceReader* software where we also classified emotions from face expressions. Since we used Tobii Studio to present our stimuli we also recorded eye-tracking data, but we do include them in our analysis.

3.2.2 Results of quantitative study

Firstly, we held a pilot study with two people. We found out that question about arousal were not clear enough so we named the answer extremes: calm and excited. Nine participants took part in our quantitative study. Every participant watched 20 videos in the same order, but we tried not to present similar videos in a row.

During exploratory analysis of the collected data, we plotted the subjective valence and arousal answers from questionnaires to the subplots for individual emotions. It is possible to see (Figure 2) that some emotions are clustered in the same part of the charts. Positioning of specific emotions also partially corresponds with valence-arousal model presented in section 2. First results of analysis show performance 36% of classifying correct emotion using our proposed approach. This result was achieved by the method where we first predicted valence and arousal values from EEG data with linear regression trained on data from [6]. Then we trained SVM classifier which classifies the individual emotions.

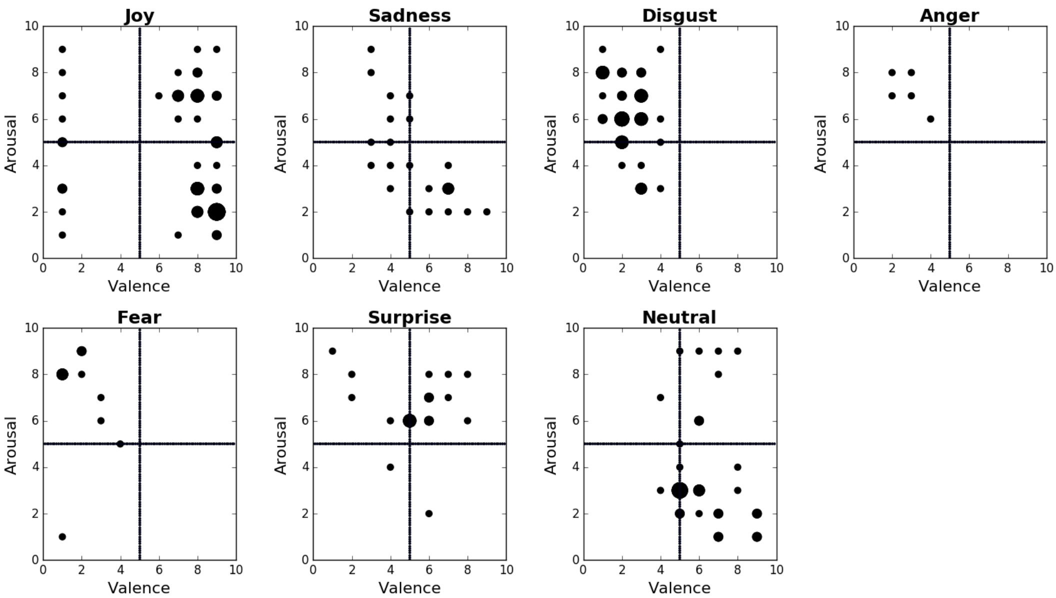

Figure 2. Subjective valence and arousal values of specific emotions from questionnaires.

4 Conclusion

In this paper we presented method for recognizing emotions from EEG signal using the EPOC Emotiv device. We used machine learning algorithm to classify the individual emotions. As a preliminary evaluation, we applied our method on the existing dataset where we achieved 37.72% accuracy when predicting one of six emotions. Then, we conducted a quantitative experiment with nine participants. First analysis shows accuracy 36%, which is not sufficient but we overcome the chance of random selection which is 14.3% (for 7 classes, i.e. six emotions plus the neutral state).

As the next step, we plan to increase this accuracy by analysing the data and improving our classification method. In addition, plan to compare our results with another approach for detecting emotions, Noldus FaceReader, to see potential of Emotiv EPOC in affective computing.

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