Emotions Detection Using Facial Expressions Recognition and EEG

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***Abstract*—The study of emotions in human-computer interaction has increased in the recent years. With successful classification of emotions, we could get instant feedback from users, gain better understanding of the human behavior while using the information technologies and thus make the systems and user interfaces more emphatic and intelligent. In our work, we focused on two approaches, namely emotions detection using facial expressions recognition and electroencephalography (EEG). Firstly, we analyzed existing tools that employ facial expressions recognition for emotion detection and compared them in a case study in order to acquire the notion of the state-of-the-art. Secondly, we proposed a method of emotion detection using EEG that employs existing machine learning approaches. We evaluated it on a standard dataset as well as with an experiment, in which participants watched emotion-evoking music videos. We used Emotiv Epoc to capture participants' brain activity. We achieved 53% accuracy in classifying a correct emotion, which is better compared to 19% accuracy of the existing facial expression based tool Noldus FaceReader.**

Keywords—emotions detection; facial expressions recognition; EEG; Noldus FaceReader; Emotiv Epoc; DEAP dataset; usability

I. Introduction

A reliable estimate of user's emotion in a particular scenario is a valuable information for any affective computing system [12], especially if it can be acquired automatically and in real time. For example, negative emotion may indicate a preliminary session exit in the context of web-based user interaction, such as searching. Personalization and adaptation of systems, though often based on users' interests, can also benefit from emotion detection, e.g., to adjust content on social channels or in learning systems [10]. Apart from that, the field of usability and user experience evaluation greatly benefits from emotion detection (e.g., it enables to detect problematic interface parts or scenario sequences that evoke negative emotion, such as frustration).

Although the automated emotion measurement is available today through variety of approaches, software and devices, none of the solutions perform ideally with respect to *accuracy*, *non-intrusiveness* and *availability*. From existing solution types, one extreme present approaches based on "traditional" user action logs. These are nonintrusive and require no special hardware (mouse and keyboard are sufficient [7]), but are in general less accurate. Another extreme represent accurate but intrusive physiological sensors (EEG, galvanic skin response, ECG, etc.) [15]. More or less a compromise, there are also approaches based on facial recognition (these are nonintrusive and rely on affordable hardware), which may use regular or depth cameras with considerable accuracy. With the arrival of affordable EEG devices, such as *Epoc* from *Emotiv* or *MindWave* from *NeuroSky* which claim to be less intrusive that the traditional EEG sensors and require less setup effort, they aim to position themselves in between the last two categories. The question remains whether they are accurate enough and suitable for the task for emotion detection, which has not yet been thoroughly researched.

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The primary concern of this paper is the emotion detection using affordable low-end EEG sensors and its comparison to facial recognition approaches. Firstly, we conducted a qualitative evaluation of two commercially available solutions employing facial expression recognition: *Noldus FaceReader* and *Shore*. Secondly, we proposed our own method of emotion detection using EEG sensor. We conducted an experiment with *Emotiv Epoc*, in which we played music videos to our participants in order to elicit their emotional response, while we recorded the EEG signal. We used the collected data to classify emotions by using machine learning and compared the results with facial expressions recognition approach for detecting emotions, namely *Noldus FaceReader*, in order to see, how these two approaches perform at the same conditions.

II. Related Work

The traditional approach (considered the ground truth in psychology) is detection of emotions with participants' self-assessment using questionnaires. Participants answer questions on Likert scale, use slider [1] or a pictorial representation, such as Self-Assessment Manikins (SAM) [4]. Because every participant has to answer all the questions and those need to be manually evaluated, it is not a very efficient method. Also, even though this can be sufficient for controlled laboratory studies, it is not suitable for real settings when the users are presented with longer stimuli with potentially changing emotional states. That is the reason for focusing on automatic emotion detection using other (implicit) responses, such as the physiological ones. Heart rate, skin conductance or pupil dilation are often used and combined [15]. However, penetration of these sensors is low and their use is currently limited only to laboratory settings.

With the exception of low-end affordable devices, this statement is mostly true also for EEG sensors, which are often used for this task as well [2]. While classifying emotions from EEG signals, many researchers focus on changes in activity of alpha and beta waves, since there is a relationship between the cognitive activity of the brain and a decrease of the activity in the alpha band [11]. However, it is in general hard to compare the different methods used, because they differ in the presented stimuli, in the used apparatus as well in the number of emotions they try to classify. For example, Takahashi [15] used headband with three dry electrodes in combination with other sensors for classifying five emotions and achieved 41.7% accuracy with the use of SVM algorithm. *Emotiv Epoc* has already been used for emotion detection, e. g., in [13]. The authors obtained the best results when using SVM with RBF kernel; they achieved around 80% accuracy, however, they did not classify a specific emotion, but only high vs. low arousal and positive vs. negative valence. Similar to our experimental task, Lin et al. [9] tried to classify four emotions that participants felt after listening to the music. They compared different classifier schemes and achieved around 90% accuracy with 32-channel EEG sensor. As to the emotion detection from face expressions, it is a well-established computer vision problem that requires the localization (and in some cases rotation) of the face in the image and its parts, such as eyes, nose, or mouth. In the past years, standard datasets were created (e.g., [5, 8]) in order to allow for comparison of algorithms, as well as commercial tools that enable to employ emotion detection in a wide range of scenarios. We analyze two of these tools in the next section of the paper.

III. Analysis of Tools for Emotions Detection Using Facial Expressions Recognition

Our first study was focused on tools that detect emotions using facial expressions recognition. We designed and conducted a qualitative case study to analyze capabilities of two software tools: *Noldus FaceReader* and *Shore*.

A. Apparatus

Noldus FaceReader[1] uses facial expressions to detect and analyze emotions. Analysis can be performed on photos and videos, which can be gathered either from a live stream or from the offline video files. As a result, *FaceReader* detects the face of a participant in a photo or a video and provides information about the participants and their experienced emotions. Besides the basic emotions (happiness, sadness, anger, surprise, fear, disgust, and neutral state), tool can also detect several personal (age, gender, and ethnicity) and facial characteristics (the state of eyes, mouth, the presence of moustache, beard, and glasses).

Shore[2] from Fraunhofer IIS provides similar features. It detects anger, happiness, sadness, and surprise. Personal and facial characteristics detection is present too. It provides real-time face detection and analysis. It can handle several specific situations, for instance rotated face detection or a detection of multiple tiny faces in the picture. Moreover, it can be also embedded as a component for another software application. The main advantage of *Shore* is that it stores information about detected faces, which is helpful especially if the participant's face is not present in the video the whole time.

Aside from these two tools, we used *Tobii Studio* to setup, conduct and evaluate our case study (we did not evaluate the collected eye tracking data). For skin conductance measuring, we used T-Sens GSR sensor together with analysis tool *Captiv*.

B. Image Annotation: Case Study

During the case study, we presented two participants with a slideshow of 16 images. We chose images from the standard dataset *GAPED* [5], which contains 730 images annotated with valence and arousal values. Each image was visible for exactly 7 seconds. During this time, participants had to decide, whether they experienced a positive or a negative emotion. They expressed their attitude by moving a mouse pointer over a slider, where the leftmost position represented the most negative value of valence, and the rightmost position represented the most positive value of valence. The environmental conditions (e.g., lighting) were the same for each participant.

To evaluate the accuracy of *Noldus FaceReader* and *Shore*, we compared emotions detected by these tools during the study. For each image we selected the emotion that was perceived by the tool with the highest percentage. In most cases both tools detected the same emotion. Since the dataset, which we used, did not contain any information about emotions, which the particular picture was supposed to evoke, we were unable to compare it with the captioned emotions. Based on our qualitative observations, both tools were similarly accurate. In addition, we compared the valence recorded by *Noldus FaceReader* and valence given by the participants. Both values were mapped to the interval [-1, 1]. Participants tended to select rather discrete values (i.e., values from {-1, 0, 1}) than continuous values. Fig. 1 shows a comparison for participant A and Fig. 2 shows a comparison for participant B. While the correlation for participant A is rather week, we see a stronger correlation between the measured and the self-assessed values in case of the participant B.

Another interesting finding was observed while evaluating the results from the skin conductance sensor. For the most cases the value of skin conductance increased right after the change of the image. We attribute this behavior to the fact that the image was unknown for the participant and therefore caused an increase of nervousness and stress. This was partially confirmed, since the increase reduced during the slideshow, which might be a consequence of the decreasing fear of the unknown. Moreover, most of the participants blinked right after the image changed. The study helped us to explore features of the both tools. Although they recognize the same emotions in most cases, the differences between measured and self-assessed values of valence suggest that they might be not as accurate; we decided to evaluate it in a quantitative study (see section VII). From the two tools, we use *Noldus FaceReader* in the rest of our work.

IV. Method of Emotions Detection Using EEG

We propose a method of emotions detection that uses EEG signal as its input. Because we aim to compare it with the existing tools, namely *Noldus FaceReader*, our method recognizes the same six emotions (joy, surprise, sadness, fear, disgust, anger) and a neutral state.

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

[2] http://www.iis.fraunhofer.de/en/ff/bsy/tech/bildanalyse/shore-gesichtsdetektion.html

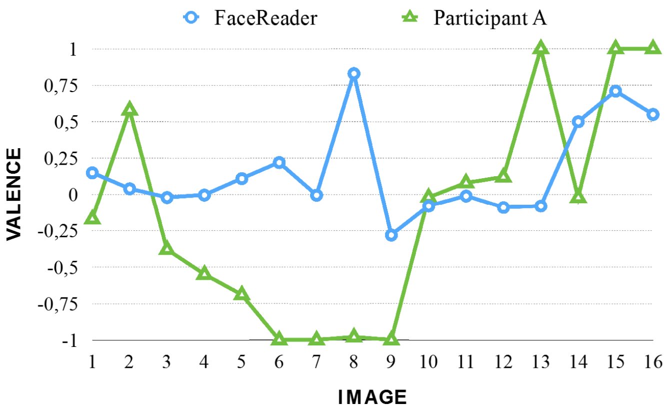

Fig. 1. Valence graph for participant A.

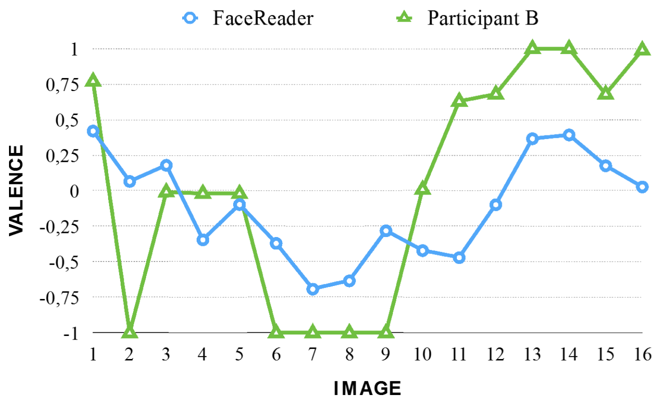

Fig. 2. Valence graph for participant B.

It is based on the well-established dimensional approach of emotions representation [14] which projects all subjective feelings into the 3D space where the dimensions are: (i) valence – positive/negative emotion, (ii) arousal – strong/weak emotion, and (iii) tension – tensed/relieved emotion. We omit the third dimension due to the difficulty of determining the amount of tension, thus reducing the model into 2D space, called Valence–Arousal model (see Fig. 3). The model divides the space into four quadrants: strong-positive emotions (I), strong-negative emotions (II), weak-negative emotions (III), and weak-positive emotions (IV) [3]. After pre-processing the EEG data, we use it to compute the strength of alpha and beta waves and the values of valence and arousal. The actual emotion detection works in two steps:

- We use the approximated values of valence and arousal computed from the EEG data to predict their "real" values, i.e., those that would be a result of a participant's self-assessment. We use linear regression for this step.
- We use the predicted values of valence and arousal as features for emotions classification. We use SVM (Support Vector Machines) classifier, which had been used in the previous works [13, 15] and can work well with high dimensional data even for small training sets.

A. Pre-processing

Before any classification we first pre-process the data. We apply DWT (Discrete wavelet Transform) on the raw EEG data

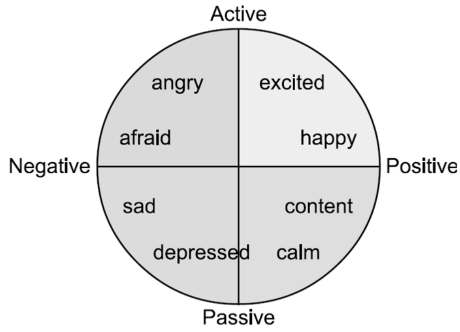

Fig. 3. Valence-Arousal model [3].

which divides the signal to the specific bands. After we have used 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 for an individual stimulus with the following formula:

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

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

B. Valence and arousal representation

Since beta waves are associated with higher brain activity and alpha waves with relaxation, high arousal is characterized by large amount of beta waves and low activity of alpha waves. So beta/alpha ratio could be indication of the state of arousal the participant is in. The beta and alpha waves appear the most and are best measurable in the frontal and the middle part of the brain as had been shown in previous research works [11], so we take signal from electrodes in this area [2, 13]:

$$Arousal = \frac{\beta_{AF3+AF4+F3+F4}}{\alpha_{AF3+AF4+F3+F4}} \qquad (2)$$

where α is a strength of alpha waves, β is a strength of beta waves, and AF3, AF4, etc. denote the individual electrodes from which the data is taken in order to compute α and β.

The psychophysiological studies show that activity in left vs. right hemisphere is associated with approach vs. withdrawal behavior and that these behaviors are in turn associated with experiencing positive vs. negative emotions respectively [11]. Therefore, based on differences in the electrical activity of the brain hemispheres, it is possible to recognize if a participant reacts to the stimulus negatively or positively [13]. We use this fact to determine the amount of valence. With alpha/beta ratio using the prefrontal electrodes, we compute the inactivity of the right hemisphere, from which we subtract inactivity of the left hemisphere in order to compute valence [2, 13]:

$$Valence = \frac{\alpha_{F4}}{\beta_{F4}} - \frac{\alpha_{F3}}{\beta_{F3}} \qquad (3)$$

C. Feature Selection

Accuracy of our method depends on how we map changes in the EEG signal to the features which we use as an input for the machine learning algorithm. Even though formulas (2) a (3) were proven to work with a certain accuracy [2], we do not to rely solely on them, but use them as one of the features for the machine learning. We also use features derived from the EEG data which 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 individual electrodes.

V. Evaluation on the DEAP Dataset

We evaluated our proposed method on DEAP dataset[3] [6] focused on the analysis of human affective states which contains data from 32 participants who watched 40 one-minute long excerpts of music videos. The EEG data were recorded with 32 electrode EEG device. To every music video, participants assigned their perceived value of arousal and valence. However, the dataset does not contain the specific emotion that the participants felt, thus rendering it not ideal for our purpose (this motivated us to create our own dataset, see section VI).

On the other hand, the dataset also contains data from online questionnaires which were used to choose the most emotional music videos for creating this dataset. The respondents chose for each video the amount of valence, arousal, and one 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. Nevertheless, we can test our method on this data and evaluate it at least partially.

A. Predicting Valence and Arousal with Linear Regression

We applied linear regression in order to predict the valence and arousal from the EEG data. We split the data into training and testing set, where testing set contained 30% of the data. We achieved low R^2 score (0.021 for arousal and 0.012 for valence) with RMSE (root mean squared error) 2.05, 2.21 respectively. However, when using the predicted values in the classification step, we obtained better results than with their original values.

B. Emotion Classification with Support Vector Machines

Next, we used the data from the online questionnaires which contained arousal, valence and emotions selected by the respondents, but no EEG data. We classified only six emotions (without neutral as this was not in the data). We were able to predict emotions with the 35.71% accuracy using our method. However, the different emotions could be predicted with different accuracies due to the differences in their sample count; so we decided to apply oversampling on the training set to make it more balanced. After this, the accuracy on the testing set slightly increased to 37.72%.

VI. User experiment with Emotiv EPOC

Because the original dataset used for evaluation of our method lacked the specific emotion, we decided to replicate the experiment carried out in [6]. In the experiment the participants watched music videos as in the original experiment, but our participants also had to choose (in the questionnaire) what emotions they felt while watching the individual music videos.

A. Experiment Setup

We conducted the experiment in the User Experience and Interaction Research Centre[4] at FIIT STU in Bratislava. For managing the experiment, we used *Tobii Studio*, where we played our videos and displayed the questionnaires. EEG data were recorded with the *Emotiv EPOC* device and *Emotiv Xavier TestBench* tool. We also recorded face of the participants using the video camera *Creative Senz3D VF0780* 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 did not include them in our analysis. Other sensor data (e.g., skin conductance) were not recorded.

At the start of the experiments, experiment instructions were shown to the participants. They were supposed to watch 20 one-minute music videos excerpts, the most of which were also used in [6] and should mainly evoke one dominant emotion (e.g., joy, sadness, etc.). Before every video, fixation cross was projected for five seconds and after each video participants answered questionnaire with three 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 did not want to force them to choose the emotion as it could skew our data. Since participants answered questions 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.

B. Experiment Process

Firstly, we held a pilot study with two people. We found out that question about arousal was not clear enough so we named the answer extremes: calm and excited.

Nine participants took part in our quantitative study, eight men and one woman. Every participant watched 20 videos in the same order, but we tried not to present similar videos in a row. Firstly, we put Emotiv EPOC device on the participant's head. It took significantly longer time to setup the device with participants with longer hair. Then we started recording the participant's face, EEG signal and play music videos. After all videos were watched we stopped recording and put EEG device down from the participant's head. Experiment with one participant took approximately 40 minutes.

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

[4] http://uxi.sk

VII. EVALUATION ON THE ACQUIRED DATASET

In our experiment, we created the dataset where we have not only subjective values of valence and arousal, but also concrete emotions. Since all nine participants watched 20 music videos, we have 180 samples. We pre-processed the data similarly to [6]. We applied bandpass frequency filter from 4 - 45Hz. Then we averaged data to the common reference.

During exploratory analysis of the collected data, we plotted the subjective valence and arousal assessments from the questionnaires to the subplots for individual emotions. It is possible to see (Fig. 4) that some emotions are clustered in the same part of the charts. Positioning of the specific emotions also partially corresponds with Valence-Arousal model (see Fig. 3).

A. Predicting Valence and Arousal

Since our dataset contains only 180 samples and we also used it to train SVM classifier, we decided to train linear regression on the data from the original dataset that contains 1280 samples of EEG data labelled with valence and arousal. After the training, we predicted the values of valence and arousal using EEG data from our experiment, which served us like a testing set. We obtained RMSE equal to 2.23 for arousal and 2.49 for valence, which is slightly worse than its performance on the original dataset. Besides AF3, AF4, F3, and F4 electrodes that should reflect the best the changes of emotions, we also tried to use all electrodes or choose a subset of electrodes with the biggest variance of alpha and beta waves power. However, those selections appeared to be less accurate.

B. Emotion Classification

We classified seven emotions using our proposed method; class distribution in our acquired dataset are in TABLE I. As

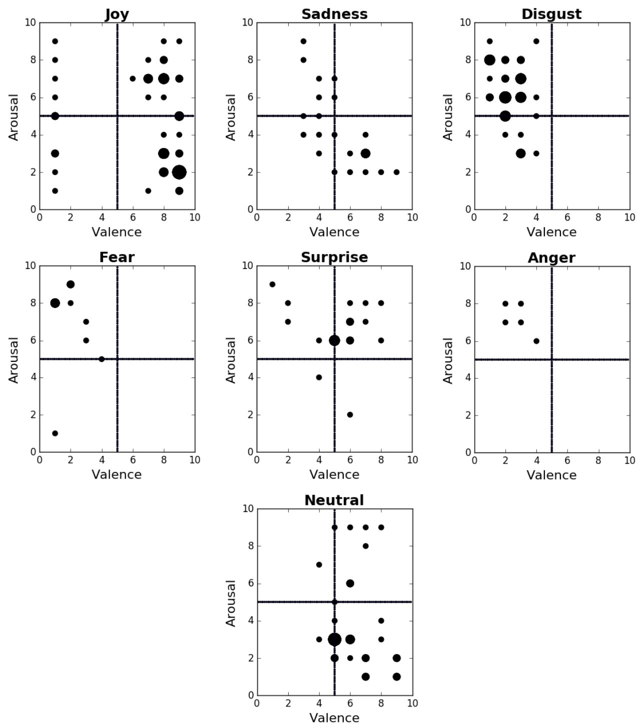

Fig. 4. Self-assessed valence and arousal values of specific emotions.

features for SVM algorithm, we used alpha, beta waves power and predicted valence and arousal values, thus combining dimensional with categorical approach. From valence and arousal values we also derived other features as described in the section IV.C. We used 5-fold cross validation for evaluation. In order to deal with unbalanced classes, we applied oversampling in the training phase, but tested it on the data, where with the original distribution of classes was preserved.

The results of our method on the acquired dataset are shown in TABLE II. We tested three kernels: linear, RBF (Radial Basis Function), and polynomial. We achieved the best accuracy 58% ±6% with the linear kernel with oversampling applied during the training. Accuracy of classifying the individual emotions is shown in TABLE III. Effect of oversampling on the classification can be seen in Fig. 5. We can see that without oversampling anger and fear were often misclassified as disgust and surprise as joy which had negative impact on the overall accuracy.

TABLE I. DISTRIBUTION OF EMOTIONS IN OUR DATASET

	Joy	Sadness	Disgust	Anger	Fear	Surprise	Neutral
#	51	22	40	5	10	19	33

TABLE II. ACCURACY OF CLASSIFYING EMOTIONS WHEN USING DIFFERENT SVM KERNELS

	Linear kernel	RBF kernel	Polynomial kernel
Without oversampling	53%	32%	37%
With oversampling	58%	42%	56%

TABLE III. ACCURACY OF CLASSIFYING INDIVIDUAL EMOTIONS

	Joy	Sadness	Disgust	Anger	Fear	Surprise	Neutral
%	47	88	59	75	57	27	41

C. Noldus FaceReader Comparison

We compared results of our method that uses EEG to the emotions detected by *Noldus FaceReader* on the videos of participants' faces recorded during the experiment described in section VI. Contrary to our method, it does not classify a single emotion, but it measures ratio of all. For comparison, we decided to always take the emotion which was measured as dominant in every music video. We found out that *FaceReader* detected mainly neutral state; for this reason, it achieved only 19% accuracy. It could have been caused by character of the stimuli that evoked weaker emotions, but also by the EEG device itself. While participants had it on their heads, it could have affected their natural (facial) reactions.

D. Emotiv Insight Comparison

In addition, we replicated the experiment procedure with *Emotiv Insight* device with another three participants. This device has five dry electrodes and it was significantly harder to maintain good quality signal than with *Emotiv Epoc* device. We achieved 30% accuracy of classifying the correct emotion. Although these results were achieved on different data, they suggest that *Emotiv Insight* is not very suitable for this specific task and *Emotiv Epoc* should be preferred.

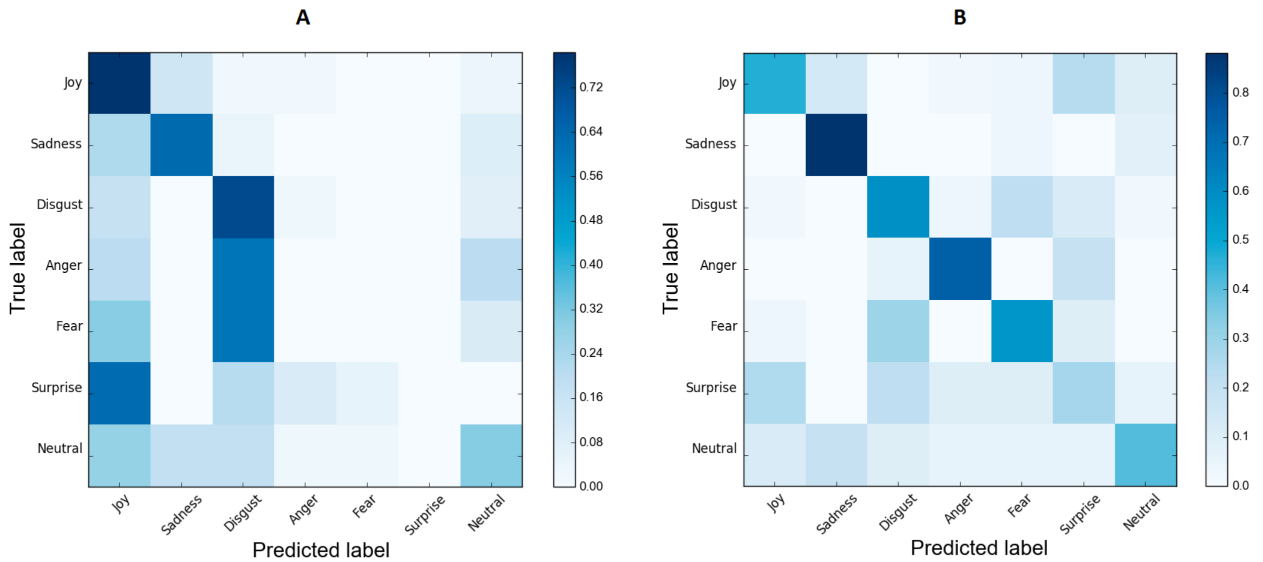

Fig. 5. Confusion matrix and effect of oversampling: (A) no oversampling, (B) with oversampling.

VIII. Discussion and Conclusions

In this paper we analyzed the existing solutions of emotion detection based on facial expressions recognition and presented our own method for recognizing emotions from EEG signal. The results achieved on the acquired dataset (58% accuracy for seven classes, i.e., six emotions and the neutral state) suggest that there is still room for improvement. However, it is important to note that we achieved them with the low-end affordable *Emotiv Epoc* device, while other works use devices with more channels or combine different physiological sensors (e.g., GSR, ECG). Also, the music video excerpts used as the stimuli might have elicited smaller emotional response, thus making it harder to correctly classify the specific emotion.

Still, the results of our method are better than those obtained with *Noldus FaceReader*. In the future, we should consider to take into account not only the dominant emotion (which was in many cases neutral), but also other recognized by the face recognition tool. In addition, we plan to combine EEG with other sensors (mainly GSR) and verify our proposed method by further experiments with other types of more realistic stimuli.

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