Detection of Negative Emotional States from Electroencephalographic (EEG) Signals

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Abstract – **We report on the development of an automated detector of negative emotional states based on 32-channel electroencephalographic (EEG) signals. The detector makes use of a fast signal parameterization technique that computes the short-term energy of the multichannel EEG signal which is combined with a state-of-the-art classification scheme based on SVM. The proposed method was evaluated on the DEAP database and we report classification accuracy of 62%. The experimental results indicate the potential of the proposed method and give an idea about the opportunities which this key technology offers in support of therapeutic treatment of emotional and psychological disorders.**

Keywords – **Emotion recognition; Electroencephalography; EEG signals; Support Vector Machine (SVM)**

I. Introduction

Emotion recognition is a key technology in support of diagnostics and treatments of emotional and psychological disorders. The traditional treatment strategy of such conditions typically involves activities for developing self-control skills in order to overcome impulsivity and impatience, which are quite common in patients with addictions, eating disorders, and other psychological disorders [1, 2].

The automated emotion recognition would greatly facilitate the medical diagnosis and treatment of psychological disorders [1-4], as it provides the means for an objective assessment of the emotional condition of a patient. Alongside medicine, other sectors of economy also exhibit interest in automated methods of emotion recognition in order to deliver user-specific performance of their products, or to allow emotion-sensitive interfaces in human-machine interaction. The largest among these are the entertainment industry and the gaming industry [5].

Electroencephalography provides the opportunity for direct monitoring and identification of emotions in the moment of their conceiving. The main challenges of emotion recognition from EEG signals are rooted in the compound nature of emotions and the multi functionality of brain.

Various machine learning techniques have been evaluated on the task of emotion recognition from EEG signals, and the Support Vector Machine (SVM) was reported to offer reliable performance. In particular, Schaaff and Schultz reported [6] on the development of an automated system, which makes use of a SVM-based classifier to distinguish between three emotional states: pleasant, neutral and unpleasant. They reported classification accuracy of 66.7%, based only on EEG signals. The reported results were obtained on a small dataset from five persons. The EEG signals were acquired with a purposely designed headband, which incorporates four electrodes built in it. The test subjets were shown pictures from the International Affective Picture System in order to induce emotions.

In [7] Li and Lu made use of linear SVM employed in a frequency search method aiming to classify EEG data in two emotional states – happiness and sadness. The test subjects were shown pictures of smiling and crying people in trials with duration 3 seconds and 1 second. They report classification accuracies of 93.5% ± 6.7% and 93.0% ± 6.2%, achieved on 10 subjects. The dataset was recorded with a 62-electode EEG cap. The electrodes were mounted inside the cap with bipolar references behind the ears.

In [8] Pin et al. reported on evaluation of different machine-learning algorithms to categorize EEG dynamics according to a subject's self-reported emotional states during music listening. They used SVM to classify four emotional states – joy, anger, sadness and pleasure and reported classification accuracy of 82.29% ± 3.06% across 26 subjects.

In [9] Petrantonakis and Hadjileontiadis present an emotion evocation and EEG-feature extraction methods. The authors tested four different classifiers (quadratic discriminant analysis -- QDA, k-nearest neighbor, Mahalanobis distance and SVM) with the use of Higher Order Crossing -- Emotion Classifier: HOC-EC. The EEG data has been gathered from 16 healthy subjects using only 3 EEG channels: Fp1, Fp2 and bipolar channel of F3 and F4 positions, according to the international 10-20 system. During the tests EEG data from a single channel and from combined channels has been used. For emotion evocation in the participants, series of facial expression images have been projected. The HOC-EC method aimed at classification of the six basic emotions -- happiness, surprise, fear, disgust, anger and sadness. The reported classification accuracy is 62.3% for the QDA method and 83.3% for the SVM classifier.

In the present paper we build on previous related work and investigate an SVM-based method for automated detection of negative emotional states. We aim to provide an objective way for detection of clearly manifested negative emotional states in support of video-game based tools for treatment of psychological disorgers. Specifically, in Section 2 we outline a simple and computationaly inexpensive signal parametrization method based on the short-term energy of multichannel EEG signal. This signal parameterization method is of particular interest as it is approprate for hardware implementation in low-energy consumption portable and wearable devices. Next, in Section 3 we provide details on the experimental setup used in the present study and in Section 4 we comment on

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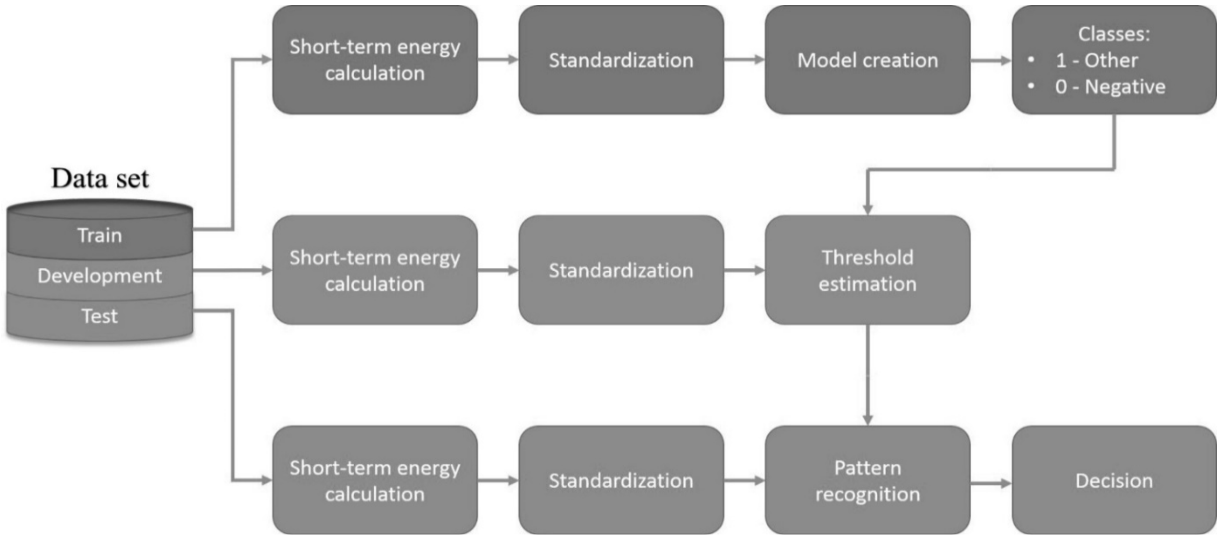

Fig. 1. Overall block diagram for the detector of negative emotional states

the experimental results. Finally, Section 5 concludes this work.

II. Negative Emotional State Detection

The proposed method for automated recognition of negative emotional states implements a classification method based on the normalized multichannel short-term energy (cf. Fig.1). The upper part of Fig. 1 presents the process of model creation, the middle part shows the threshold estimation, and the lower part illustrates the processing steps during the operation of the detector. These three processes share a common feature extraction stage, described as follows:

First, the EEG signal $x_i(n),\ i = 1,2,...32,$ is pre-processed for reducing the interference from muscular and eye movement activity, which results in the free of artifacts EEG signal $\hat{x}_i(n),\ i = 1,2,...32$. Next, the short-term energy E_i is computed for each EEG channel. This is performed by means of a sliding window of 343.75 milliseconds with skip rate of 85.9 milliseconds (i.e. overlap 75% between successive frames) which is applied on the pre-processed signal. The overlap of 75% between subsequent frames provides a smooth estimation of the energy. The short-term energy E_i for a frame of K successive samples is computed as:

$$E_i(p) = \sum_{k=1}^{K} \left(\hat{x}_i(pL+k)\right)^2, \qquad (1)$$

where $\hat{x}_i(.)$ is the pre-processed EEG signal for channel $i = 1,2,\ldots 32$; L is a predefined step size which defines the degree of overlapping between two successive frames; and $p = 0,1,\ldots P-1$ is the frame index. Here, the number of successive overlapping frames in a recording with length N samples is computed as

$$P = \mathrm{fix}\left(\frac{N-K+L}{L}\right), \qquad (2)$$

where the operator **fix** stands for rounding towards the smaller integer number.

Subsequently, the short-term energy E_i estimated by (1) is post-processed for reducing the undesired fluctuations due to time-varying recording conditions. For this purpose statistical standardization of E_i is performed, i.e. the distribution of the short-term energy is normalized to zero mean value and unit standard deviation. The result of applying statistical standardization on E_i is the z-score of each individual parameter for the 32 dimensional feature vector:

$$Z_i(p) = \frac{E_i(p) - \mu_i}{\sigma_i}, \quad i = 1,2,\ldots 32, p = 0,1,\ldots P-1. \qquad (3)$$

The z-score, computed through (3), quantify the distance from the mean in terms of the standard deviation. The mean value μ_i and the standard deviation σ_i are estimated on per recording basis for each of the 32 EEG channels. The standardized 32-channel z-score are next used to build a person-specific SVM classifier, which is trained to distinguish negative emotional states (tagged with “0”) against other (neutral and positive) states (tagged with “1”).

Once these models are built, we make use of a development dataset in order to estimate the recording-level decision threshold (Fig. 1, middle part). The decision threshold *Tr* is person-specific and is computed as

$$Tr = \frac{\frac{1}{n}\sum_{k=1}^{n} D_{neg,k} + \frac{1}{m}\sum_{l=1}^{m} D_{pos,l}}{2}, \ [\%] \qquad (4)$$

where *Dneg* and *Dpos* are the portions of development data consisting of n recordings with negative tags and m with other (neutral or positive).

Once the decision threshold is computed, the detector of negative emotional states is ready for operation. During nominal operation, the short-term energy of the input recordings is computed (1) and then is standardized (3). Based on the individual z-score vectors with dimensionality 32, the pattern recognition stage makes frame-by-frame decision about the class belonging of each vector. The outcome of this process is a vector of *P* decisions, where *P* depends mainly on the length of the EEG signal, and the selected inter-frame step size *L* in (1). In order to make decision for an *entire EEG recording*, we estimate the ratio of the decisions “0” to the total number of decisions *P* and then apply the decision threshold (4).

When the proportion of "0" is above the decision threshold, the EEG recording is classified as negative emotional state.

III. EXPERIMENTAL SETUP

We made use of an experimental protocol based on the Database for Emotion Analysis using Physiological signals (DEAP) [10]. The DEAP database consists of recordings from thirty-two participants with a total of 40 recordings per participant. Each recording, made while the participants were watching musical video-clips, consists of 40 channels. These include 32 EEG channels, electromyographic (EMG), electrooculographic (EOG) and other channels, all taken from different parts of the head and the body. The database includes original and preprocessed recordings from these forty channels. Frontal face videos and detailed metadata for the participants are also included in the database.

The EEG signals have been recorded with a sampling rate of 512 Hz and afterwards have been downsampled to 256 Hz and filtered using a second order high-pass filter with cut-off frequency 2 Hz. Artifacts due to eye-movement and muscle-movement have also been removed. Only the ending 30 seconds of each EEG recording were kept.

The annotations in the DEAP database are based on self-reporting of the participants. Each person rated her/his feelings related to a specific video-clip on a scale between 1 and 9, where 1 is the lowest rating (dislike, negative feelings) and 9 is the highest (like, positive feelings).

In the present work we consider a person-specific emotion recognition setup and made use only of the 32-channel EEG recordings of 10 people for which there are at least 30 suitably tagged recordings. We split up the recordings of each person into two categories –*negative* emotions and *other*– depending on his/her opinion ratings. Here we consider the recordings with rating below 4 as category *negative* (disliked) and these with ranking above 4 as category *other*. Ratings between 4 and 5 were not clearly identified as positive or negative and either provoked mixed feelings or the participant feelings were not definite. Because of that we didn't apply a strict threshold during the initial selection of recordings for each person but instead aimed to collect as many recordings as possible without breaching the common sense rules used during the video-clip rating. Specifically, for the purpose our experiment we have chosen only these participants for whom there is sufficient amount of tagged recordings and at least 13 recordings in the category *negative*.

Furthermore, we split the recordings of each person in three parts: (i) training, (ii) development and (iii) testing datasets. These three splits have 20% of the data for training the person-specific models, 20% used as development data for adjusting the person-specific threshold (4), and the other 60% as a test dataset. However, depending on the total number of tagged recordings for each participant, these percentages varied with up to 5%.

In general, the training dataset consisted of 4 recordings with negative tags and 4 (or in some cases 5) recordings with other tags (neutral and positive). During initial tests it was observed that maintaining such a balanced training dataset contributes for the improvement of the classification accuracy. Only recordings that are most representative for the two categories of emotional states were chosen for the training datasets -- starting with recordings with ratings closest to 1 or 9 and continuing up or down until the desired number of recordings is reached.

The development dataset, consisting of 8 or 9 recordings per person was used for the adjustment of the person-specific decision threshold (4). For that purpose, n=4 (in certain cases n=3) recordings tagged as *negative* and m=5 recordings tagged as *other* were used.

The total amount of recordings in the test dataset is N_{rec}=227, i.e. approximately 23 recordings per person (cf. Table 1).

A person-specific classifier was built from the training dataset and was tested only with the test dataset of the same individual. The short-term energy was computed (1) for a window with K =88 samples sliding with a step of L =22 samples as this was observed to provide the best results. For each test recording of length N=8064 samples, the person-specific decision threshold (4) was applied on the histogram of the P=363 frame-based SVM output scores in order to make decision about the class belonging of that recording.

The classification performance is evaluated in terms of percentage correct detections:

$$correct = \frac{H}{N_{rec}} \times 100\%, \tag{5}$$

where N_{rec} is the total number of test recordings and H is the number of correctly classified recordings.

IV. RESULTS

Following the experimental protocol described in Section 3 we report the experimental results for the proposed method (Table 1). The first column in the table refers to the participant number in the original DEAP database. The second, third and forth columns show the overall number of 30-second EEG recordings used for training, development and testing, respectively. The fifth column presents the number of *hits*, i.e. how many times the proposed detector correctly recognized the class belonging of the test recordings and the sixth column provides the classification accuracy computed as the *percentage correct* (5).

As it can be seen, the classification accuracy differs significantly among the 10 individuals. The average classification accuracy for the ten participants is 62%, where the lowest individual percentage correct is 54.5% and the highest individual percentage correct is 73.9%.

Among the major reasons for such a great difference in the classification performance is that recordings which were tagged with the same ratings have considerable differences in the dynamics of the EEG signals even for the same person. Furthermore, the self-reporting of emotional states, which was used for recording tagging in the DEAP database, seems to be a tricky process as calibration of responses among the different participants seems to be quite difficult.

TABLE 1. CLASSIFICATION ACCURACY FOR 10 PERSON-SPECIFIC DETECTORS OF NEGATIVE EMOTIONAL STATES

Participant №	№ of training data	№ of development data	№ of testing data	№ hits	Correct [%]
2	8	8	24	15	62.5 %
11	10	8	22	12	54.5 %
17	9	9	22	14	63.6 %
21	8	9	23	13	56.5 %
22	9	9	22	12	54.5 %
24	9	9	22	14	63.6 %
28	8	8	24	15	62.5 %
29	8	9	23	15	65.2 %
30	8	9	23	17	73.9 %
32	9	9	22	14	63.6 %
Average correct					62.0%

V. CONCLUSION

The proposed computationally inexpensive automated detector of negative emotional states, which is based on 32-channel electroencephalographic (EEG) signals, shows that there are significant variations among the EEG activity of people who like or dislike certain video-clip. The classification accuracy of 62% is insufficient for many practical applications, yet we deem that after averaging a number of subsequent measurements it can be of certain use. Further improvement of classification accuracy would require elaboration of the signal parameterization process and computation of a larger set of relevant features from the EEG signal. In conclusion, we deem that the experimental results indicate the potential of the proposed method as a candidate technology which could find certain use in support of video-game based treatment of emotional and psychological disorders.

ACKNOWLEDGEMENTS

The authors acknowledge with thanks the financial and logistic support by the project OP "Competitiveness" BG161PO0031-1.2.04-0044 financed by the Structural Funds of the European Union, and by the project ISP1 financed by the Technical University of Varna, Bulgaria. The first author acknowledges with thanks the financial support by the OP "РЧР" BG051PO001-3.3.06-0005.

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