Classification of Basic Human Emotions from Electroencephalography Data

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Abstract. This paper explores the combination of known signal processing techniques to analyze electroencephalography (EEG) data for the classification of a set of basic human emotions. An Emotiv EPOC headset with 16 electrodes was used to measure EEG data from a population of 24 subjects who were presented an audiovisual stimuli designed to evoke 4 emotions (rage, fear, fun and neutral). Raw data was preprocessed to eliminate noise, interference and physiologic artifacts. Discrete Wavelet Transform (DWT) was used to extract its main characteristics and define relevant features. Classification was performed using different algorithms and results compared. The best results were obtained when using meta-learning techniques with classification errors at 5 %. Final conclusions and future work are discussed.

Keywords: Electroencephalography · Discrete Wavelet Transform · Human emotion classification

1 Introduction

Recently, scientific development has been enhanced by the application of the interaction between different research paradigms to help understand complex phenomena in a field of study. For example, the use of neuroscience techniques to model human behavior in different areas [1]. Usually, research on emotion analysis is based on facial expressions and voice analysis (discourse). [6]. However, there are ways to alter those tests by masking real emotions or faking emotions in an interview. To avoid this issue there has been growing interest in the use of physiological data such us the EEG [2]. Ekman [5] and Winton [6] found the first evidences of physiological signal changes in relation to a small set of emotions. Cacioppo [4] identified patterns within the physiological signals with statistical significance to emotional changes on humans. An EEG system records electrical signals on the scalp generated by brain activity [9]. These signals are voltage variations due to ionic currents caused by neuronal activity in the brain [8].

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EEG signals are usually separated by its frequency content in 5 types. Delta signals with frequencies up to 4 Hz and larger amplitude (250 to 325 μV). Theta signals in the range between 4 an 8 Hz. Alpha signals cover the range between 8 and 14 Hz and characterize relax and alert states. Beta waves, with a frequency range between 14 and 32 Hz is related to motor activity. Gamma waves are the fastest, with a frequency range in between 32 and 100 Hz [8]. With so many interactions between neurons in the brain plus muscular activity and outside interference, these signals have a relatively low signal to noise ratio. To gather useful information from EEG data needs special equipment but also specific signal processing techniques [3,7,15,22]. On the other hand, it is a non invasive technique with a simple setup, relatively low cost and temporal high resolution potential that makes it ideal for engineering and clinical applications. There are commercial products that use EEG data for different applications such as games, rehabilitation [11] but mostly there is not detailed information on how they do it, making it difficult to use on research. This work makes use of a medium range commercial platform to gather EEG data from a designed experiment on 24 subjects and presents a signal processing strategy applying wavelet theory and meta-learning techniques to classify four basic human emotions.

The paper is organized as follows: section 2 explains the methodology used, equipment, population and experiment protocol. Section 3 describes the signal processing techniques employed to classify the emotions present in the data. Results are presented in section 4. Finally, conclusions and future work are presented in section 5.

2 Methodology

2.1 Population

EEG signals were recorded from 24 subjects between 22 and 39 years of age, 16 male and 8 women. None of them had any history of physical or mental illnesses nor were taking any drugs or medication that could affect EEG data. All subjects were informed of the scope and objectives of the test and signed an informed agreement with a detailed explanation of the test. Besides, any subject could leave the experiment at any time if desired.

2.2 Experimental Setup

EEG data was measured and recorded using an Emotiv EPOC headset with 16 channels, although two of them were used as reference [10]. Ag/AgCl electrodes were placed on the subject's scalp using the international 10-20 standard convention [9]. Sampling time selected was 128 Hz. The headset is connected to a PC which receives the time sequences corresponding to each channel. The sequences are preprocessed in the device with 2 notch filters at 50 and 60 Hz to eliminate power line interference and a passband filter of 0.16-45 Hz bandwidth. The device also gives a measure of the contact quality on each channel. Data was discarded if contact quality on a given channel was no good.

2.3 Test Protocol

The subjects were sat in front of a PC running the Psychopy [12] application with the headset correctly placed. A sequence of 12 audiovisual clips was presented to the subjects to elicit 4 emotions: rage, fear, fun and neutral (or absence of emotion), with 3 clips per emotion. The clips were selected from FilmStim [13], a free stimuli database. Each clip, taken from a commercial film, has been validated to elicit a specific emotion, even for spanish speakers [14,18]. The order of clips in the sequence is such that consecutive clips can not evoke the same emotion. In between clips a short survey with 3 SAM images [19] is given for relaxation and in order to neutralize the effects of one clip on the next. Three 12-sequence audiovisual protocols were generated using the same 12 clips in different order, randomly selecting one for each subject. The experimental process is summarized in Fig. 1. The whole test took between 30 to 45 minutes to complete for all subjects.

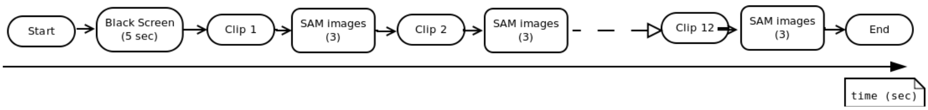

Fig. 1. Test protocol presented to each subject: a sequence of 12 audiovisual clips to elicit a specific emotion alternated with a survey of 3 SAM images.

3 Data Classification Process

3.1 Preprocessing

EEG raw signal is contaminated with noise and artifacts of external and physiologic origin. Emotiv EPOCH acquires and filters the raw data with notch filters in 50 and 60 Hz to eliminate interference from the power line and a passband filter with 0.16-45 Hz bandwidth [10]. There are still non desired artifacts in the channel signal as shown in Fig. 2.

First, the EEG raw data obtained from Emotiv for each subject is segmented in time in 12 pieces corresponding to each clip. To further eliminate artifacts such as eye and eyebrow movements and neck muscle activity the `clean_rawdata()` wrapper function from the Artifacts Subspace Reconstruction (ASR) extension to the EEGLAB Matlab Toolbox was applied [20]. Normalization of the filtered data was performed before extracting the main features to use for classification.

3.2 Feature Extraction

Preprocessed data is still too big and complex to be able to discriminate emotions from them directly. A set of relevant features needs to be extracted to minimize classification mistakes. Because EEG data is a strongly non-stationary signal

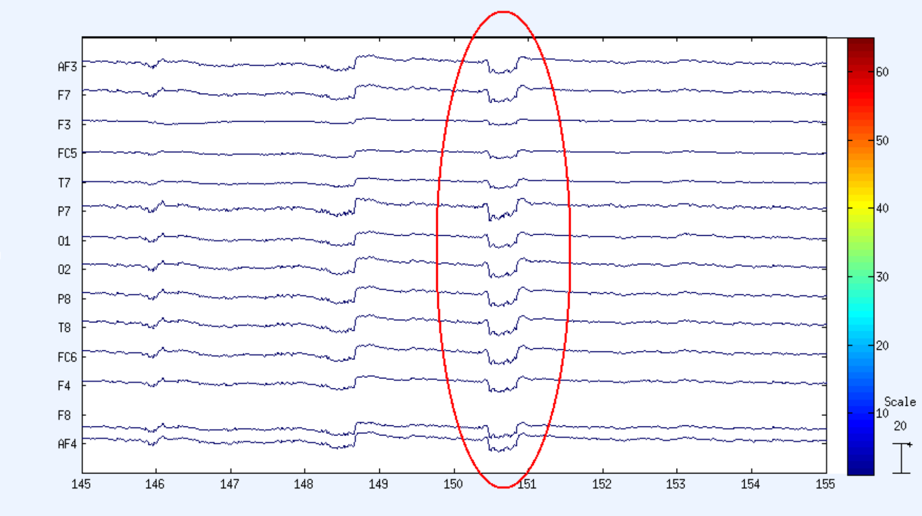

Fig. 2. Raw data from all 14 active headset channels showing ocular artifacts (red oval).

a multi-resolution analysis method using a Wavelet Transform is selected to compress the data without losing too much information from it as proposed in [17,21,22]. DWT uses a mother wave $\Psi(t)$ to generate the basis for decomposition of the time sequences recorded from EEG signals. Three mother waves were selected, two from the Daubechies family (db4, db8) and one from the Symlet (sym8) because they provided acceptable time-frequency resolution [23,24]. The basis is generated using two integer parameters j and k, the scale and translation indexes, giving the wavelets

$$\Psi_{j,k}(t) = \Psi(2^j t - k), \quad j = 1, \ldots, n \quad k = 1, \ldots, N, \tag{1}$$

with N the number of samples and n the number of decomposition levels. Since the sampling frequency is 128 Hz, $n = 14$ decomposition levels were used to have sufficient discrimination for the 5 types of EEG waves. Each EEG preprocessed sampled data per subject, channel and clip $s(t)$ can be expressed in terms of the wavelets as

$$s(t) = \sum_{k=1}^{N} \sum_{j=1}^{n} d_j(k).\Psi_{j,k}(t). \tag{2}$$

The coefficients $d_j(k)$ were computed using the Quadrature Mirror Filter Bank [22]. Based on the coefficients $d_j(k)$ the following features were computed:

1. **Power**. The power of the signal for each frequency decomposition level j.

$$P_j = \frac{1}{N} \sum_{k=1}^{N} |d_j(k)|^2, \quad j = 1, \ldots, n. \tag{3}$$

2. **Variance**. A measure of the variation of the coefficients of the signal for each frequency decomposition level j.

$$V_j = \frac{1}{N}\sum_{k=1}^{N}(d_j(k) - \bar{d_j})^2, \quad j = 1, \ldots, n. \tag{4}$$

   with $\bar{d_j}$ the mean value of the coefficients $d_j(k)$ of the signal for a level of decomposition j over all k.
3. **Entropy**.

$$H = -\sum_{j=1}^{n} p_j \log(p_j) \tag{5}$$

$$p_j = \frac{E_j}{E_T}, \quad j = 1, \ldots, n, \tag{6}$$

   with E_j the energy in the jth frequency band and E_T the total energy.

In summary, for each EEG channel and clip, $2n + 1$ features are generated.

3.3 Classification Process

Pattern classification algorithms associate each element, i.e. each set of feature values characterizing the current emotion of a subject, with one of the 4 emotions analyzed. In this work a comparison of the best classifiers used for a similar problem in previous works was carried out [16,21]. Those were: K-nearest neighbors (KNN), AdaBoost and Random Committee. KNN is a nonparametric classifier where a decision for an individual value is taken by looking at which classes its K nearest neighbors are and voting. It is robust to outliers. K values between 2 and 8 were tried to find the optimum (K=3). AdaBoost is a supervised learning algorithm that combines weak classifiers to generate a strong classifier. It is robust to overfitting but sensible to outliers [25,26]. The best results were reached when using the kernel called J48 [28]. RandomCommittee is a technique within the framework of metalearning algorithms. It takes existing classifier systems and generates an ensemble of instances of classifiers using random parameters that are embedded in the base classifiers selected. The classification is made by either voting or averaging the results of the ensemble of classifiers generated.In this work the best results were obtained when using RandomForest as the base classifier and averaging their results [27]. Classification was performed using the tool WEKA [29], using 10-fold cross validation and pattern testing with 10 percent fresh data.

4 Results

The tables below show the results as percentage of correct classification and ROC area for each class, and total percentage of correct classification for the three classifiers selected.

Table 1. Classification accuracy when using KNN method with k=3.

	db4		db8		sym8	
	%	ROC	%	ROC	%	ROC
Correct Classification (%)	79.9		73.4		59.4	
Fear	70.0	0.900	63.8	0.820	44.7	0.734
Rage	80.0	0.819	74.1	0.846	45.8	0.704
Fun	77.4	0.924	64.7	0.845	58.3	0.805
Neutral	98.1	0.992	96.2	0.991	98.2	0.994
Weighted Average	81.0	0.909	74.3	0.874	60.2	0.807

Table 2. Classification accuracy using Random Committee with Random Forest kernel.

	db4		db8		sym8	
	%	ROC	%	ROC	%	ROC
Correct Classification (%)	94.3		91.8		84.6	
Fear	87.5	0.989	83.1	0.978	73.3	0.949
Rage	96.5	0.993	91.5	0.992	89.4	0.939
Fun	94.8	0.990	88.3	0.983	83.0	0.947
Neutral	100	1.00	98.3	1.00	98.0	0.999
Weighted Average	94.5	0.975	92.1	0.960	85.5	0.958

Table 3. Individual Classification Accuracy when using AdaBoostM1 with kernel J48.

	db4		db8		sym8	
	%	ROC	%	ROC	%	ROC
Correct Classification (%)	87.3		82.4		77.9	
Fear	89.5	0.956	76.6	0.932	73.3	0.899
Rage	83.3	0.986	83.6	0.980	69.5	0.899
Fun	81.8	0.974	76.6	0.944	75.8	0.951
Neutral	96.4	0.985	94.5	0.987	98.2	0.995
Weighted Average	87.8	0.975	82.6	0.960	78.2	0.935

Table 4. Confusion matrix for Random Committee for db4 feature set.

	Fear	Rage	Fun	Neutral
Fear	64	0	2	0
Rage	6	53	0	0
Fun	5	0	55	0
Neutral	0	2	0	57

For the three types of wavelets selected the Random Committee classifier obtained the best results. Within each classifier, the wavelet of type Daubechies with 4 vanishing moments (db4) outperform the others, reaching 94.3 % of overall correct classification percentage for the Random Committee classifier. ROC values are mostly acceptable at around 90 % in all cases and higher than 97 % for the best results. Finally, the best classifier reached 87.5 % classification accuracy on the test set. Looking at the emotions themselves, the neutral emotion was the easiest to discriminate for any classifier throughout. On the other hand, the Fear emotion seems to dominate over Rage and Fun according to Table 4.

5 Conclusions

This work presents a system to record, analyze EEG signals and classify basic human emotions. An experiment was conducted using 24 subjects with a validated database of audiovisual clips to induce rage, fear, fun or neutral emotions. Even though the hardware only allowed to sense 16 channels compare to research devices with 64 up to 256 electrodes, by an adequate signal processing using DWT and relevant features, the overall percentage of errors achieved was around 5 % when using meta-learning techniques. Some of the mistakes between classes might be due to a smaller train set or the clips themselves that were in some cases too long and with mixed feelings to clearly represent the emotion assigned even though the dataset has been validated internationally. The study allowed to see the impact in classification of the selection of features, algorithms for eliminating artifact in the signals and wavelets selected. The results are promising to consider an EEG system like this one a relatively low cost new complex sensor device for research into other bioengineering areas. From a practical point of view, the use of shorter clips should be better to have less dispersion in the data. Also, to have more subjects will improve the statistics. Future work includes the use of other techniques to improve the elimination of artifacts such as independent component analysis, to reduce the dimensionality of the problem in the feature space and the application of this sensor in neuromarketing and rehabilitation engineering.

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