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Emotion Detection Using EEG Signals

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Abstract—**In this paper we propose some new methods for detecting emotions in EEG signals, using both time analysis and frequency analysis of signals. In the last section of the paper we present a method of classifying EEG signals using a feedforward neural network. EEG signals were acquired on a single channel, using a laboratory equipment produced by BIOPAC, and the subject was relaxed with his eyes open or in one of the states of joy, anger, and music listening for about 60 seconds. Separate analyzes were also performed for the 4 frequency bands of the EEG signals: alpha, beta, theta and delta waves.**

Keywords—electroencephalography, zero crossings, discrete cosine transform, neural networks, emotion detection

I. INTRODUCTION

Emotion detection is currently a field of research of great interest due to the many possible applications, such as lie detectors, patient monitoring, establishing preferences in viewing media products, human-computer interfaces, and so on. In addition to the use of EEG signals, other classification methods have also been proposed, such as speech analysis, skin conductance, face expression, body movement analysis, and other electrophysiological signals like ECG [1].

Emotion recognition based on EEG features in movie clips has been studied in [2], and the effect of listening to music on EEG signals has been described in [3] and [4]. Reference [5] proposes the reduction of parameters that describe EEG signals using Discrete Cosine Transform (DCT). A method of classifying EEG signals using an adaptive transform, called by the authors the Empirical Wavelet Transform (EWT), and a fuzzy classifier is proposed in [6]. The application for which this method was proposed is a brain computer interface. References [7] and [8] propose the use of a neural network for the classification of EEG signals.

In this paper we aim to discriminate the state of relaxation with open eyes, from one of the following emotional states: joy, anger, listening to a piece of music by Chopin and listening to a rock song by the band Queen. EEG signals were recorded using a laboratory MP36 Biopac Acquisition Unit using a single channel with A/D sampling resolution of 24 bits, sample rate of 1000 samples/s, and the signal to noise ratio greater than 89 dB. The unit directly provides the separation of the recorded signals in frequency bands: alpha (8-13 Hz), beta (13-30 Hz), theta (1-5 Hz) and delta (4-8 Hz). EEG signals were recorded from the parietal area (electrodes F4 and P4), during 60 seconds. These EEG signals have also been used in papers [1] and [9].

In this paper we compare an EEG signal in a relaxed state with an EEG signal picked up in an emotional state. We will analyze the number of zero passes and the sample averages of the two EEG signals. Then we will calculate Fast Fourier Transform (FFT) and DCT for the two signals and we will compare the samples of the obtained spectra. Finally, in the last section of the paper we will use a neural network to classify signals.

The paper is organized as follows: section II describes two methods of classification using time analysis of EEG signals, section III deals with frequency analysis of signals, and section IV presents a classification method using a neural network with a hidden layer. Section V concludes the paper.

II. Classification of EEG Signals using Time Analysis

In Fig. 1 we represented 60000 samples from a real EEG signal in the relaxed state. The signal represented in Fig. 2 is recorded with the same electrodes, but in a state of rage, and the acquisition was also made during 60 seconds with a sampling rate of 1000 samples per second.

A simple method by which we can compare two signals that have the same number of samples would be to count the passes through zero for each of the two signals. If we admit that the signals do not have a continuous component, then it is enough to compare every two neighbouring samples, and if their product is negative, then to increment a variable that will eventually contain the number of zero crossings for that signal.

Another method of comparing two signals over time is to calculate the average value of the signal samples over a period of time, in our case also 60 seconds, using the following equation:

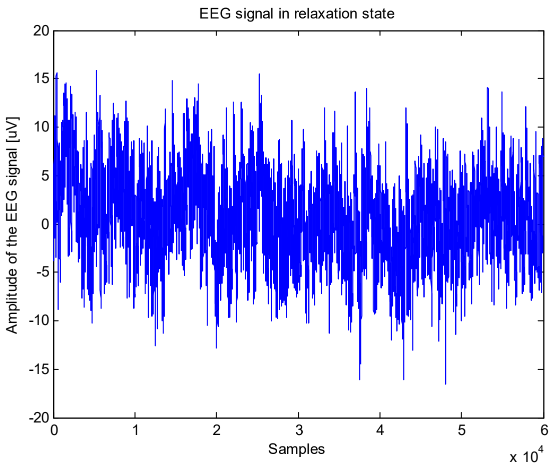

Fig. 1. EEG signal in relaxation state (60000 samples, that is 60 seconds).

$$mean = \frac{1}{nr\_samples} \cdot \sum_{i=1}^{nr\_samples} \left| signal(i) \right| \qquad (1)$$

where *nr_samples* is the number of samples from the signal, and *signal*(*i*) is the value of sample *i* from the signal. *Signal* is the whole EEG signal or only its components, i.e. the alpha, beta, theta and delta waves.

The zero crossing numbers for each of the EEG signals and their components are calculated and represented in TABLE I. In the first column on the left are given the 5 emotional states, and in the adjacent columns are given the average values of the amplitudes for the EEG signal and its component waves.

TABLE I. The Zero Crossing Numbers For EEG Signals

State	EEG signal	Alpha wave	Beta wave	Theta wave	Delta wave
relaxation	1764	1725	2629	1191	278
joy	1905	1767	2664	**1268**	**300**
anger	1863	1784	2637	1279	**323**
Chopin	1752	1784	2615	1186	259
Queen	1814	1736	2757	1096	**260**

From these data we notice the presence of higher frequencies in the states of joy or anger, while listening to some musical pieces does not influence too much the state of relaxation. But the most pronounced increase in frequency, of about 8% for the global signal, is observed in the case of the state of joy, which is mainly due to the increase of theta and delta waves. In the state of anger we find also an increase in frequency of about 5.5%, due to the increase in delta waves (by about 14%).

In [10], the author R. Douglas Fields recalls experiments in which there was a significant increase in oscillations of 4 Hz (that means theta and delta waves) in the case of laboratory mice that were subjected to strong negative stress (feelings of fear).

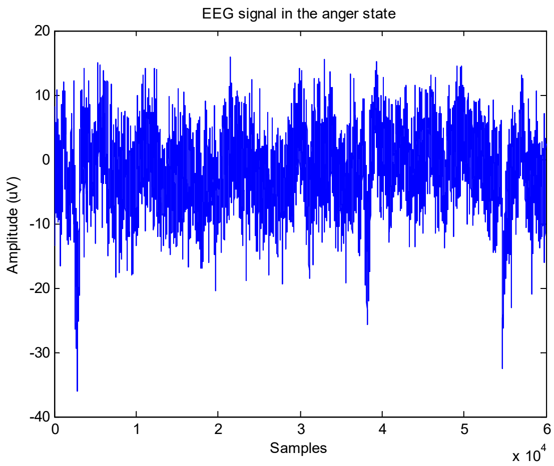

Fig. 2. EEG signal in the anger state (60000 samples, that is 60 seconds).

The calculated results for the average value of the signal samples over a period of time were listed in TABLE II.

TABLE II. MEAN OF THE AMPLITUDES IN MICRO VOLTS

State	EEG signal	Alpha wave	Beta wave	Theta wave	Delta wave
relaxation	3.450	1.107	1.612	0.891	1.638
joy	4.003	1.388	2.088	1.039	1.577
anger	4.649	1.534	2.298	1.152	1.859
Chopin	3.968	1.131	1.650	0.928	1.916
Queen	3.212	0.986	1.488	0.878	1.644

We notice from this table that the average amplitude for the state of joy is 16% higher than the same parameter in the state of relaxation (the contributions of alpha and beta waves being over 25% higher), and for the state of anger, the difference is 34% for the global EEG signal (here in addition to the alpha and beta waves, the contribution of theta waves also exceeds 30%). Listening to some pieces of music changes the average amplitudes less (an increase of 14% for Chopin and a decrease of 6% for Queen, i.e. the emotion for Chopin seem higher than for Queen).

III. CLASSIFICATION OF SIGNALS USING FREQUENCY ANALYSIS

The Fourier spectrum of the alpha waves from the EEG signal in the joy state is represented in Fig. 3. We also calculated in this case the average values of the samples using equation (1) and we found that the highest averages of the Fourier spectrum samples are also found in the state of anger; they exceed the averages in the state of relaxation by over 40% for alpha and beta waves. In the state of joy there is also a significant increase of these average values compared to the state of relaxation, with over 20% for alpha waves and about 30% for beta waves.

Fig. 4 represents the DCT transform for the same signal. It can be seen that the number of significant samples of the transform is much smaller than in the case of FFT, therefore we could use this information to extract a smaller number of features.

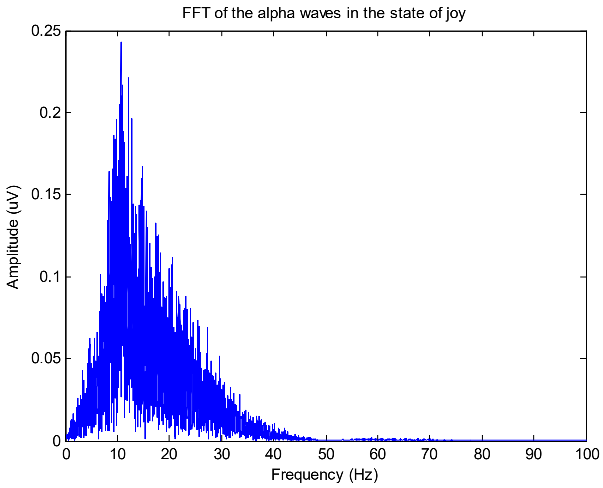

Fig. 3. Fourier spectra of the alpha waves in the state of joy.

The mean values of the first 5000 samples of the DCT transform are given in TABLE III.

TABLE III. MEAN OF THE SAMPLES IN DCT TRANSFORM [MICRO VOLTS]

State	EEG signal	Alpha wave	Beta wave	Theta wave	Delta wave
relaxation	9.532	2.999	4.859	2.262	2.213
joy	11.566	3.756	6.253	2.643	2.267
anger	13.227	4.204	6.921	2.996	2.789
Chopin	10.493	3.176	4.956	2.415	2.652
Queen	9.026	2.774	4.528	2.161	2.171

We find that there are about the same conclusions as in the case of Fourier transform. The maximum values of the averages in the state of anger are even 40% higher than the values in relaxation, especially for alpha and beta waves. In the state of joy this increase is over 25%, both in the case of alpha and beta waves, while for the two pieces of music the variations are much smaller. We find again that the emotions given by the states of joy or anger are greater than those produced by listening to musical pieces.

IV. CLASSIFICATION OF SIGNALS USING A NEURAL NETWORK

We propose to use a multi-layer feedforward neural network to classify EEG signals. The architecture of the neural network will consist of a single hidden layer that will contain 5 or 10 neurons. The information applied at the network input consists of the DCT coefficients of the EEG signals, which contain in a small number of samples all the essential information existing in the signal. We will choose a number of 10 input neurons, each input value being an average of a number of samples, and 2 output neurons decide the membership classes for the input signals.

The comparisons will be made as before, between the state of relaxation and each of the other 4 states. Unfortunately we don't have a sufficiently large database of signals to train the network.

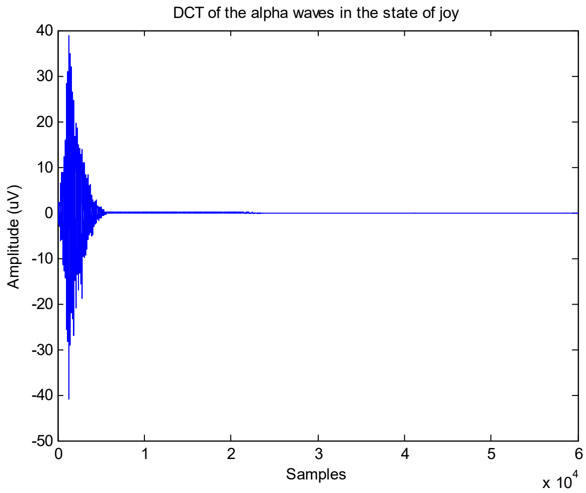

Fig. 4. DCT of the alpha waves in the state of joy.

In order to have a sufficient number of drive data, we will divide each analyzed signal into intervals of 500 ms. Therefore, in 60 seconds we will get 120 data sets for each signal.

A portion of 500 samples of the EEG signal generated in the relaxed state is represented in Fig. 5, and DCT of this EEG signal can be seen in the Fig. 6. As we can see from this figure, the first 50 samples contain almost all the signal energy, and for the alpha, beta, delta and theta waves the essential number of samples is even smaller. Therefore, we will retain only 10 coefficients of transformation, which will be the inputs to the neural network. These coefficients are obtained by averaging each group of 5 samples in the range of 1 to 50 samples considered. The network has two binary outputs: their values are 1 and 0 for one of the states, respectively 0 and 1 for the other.

The database generated in this way consists of two matrices: one consisting of 10 rows and 240 columns (rows are the coefficients of discrete cosine transformation, and the columns are given by the 240 signals of 500 ms each) and a binary matrix of 2 rows and 240 columns representing the output values. Network training is done with a set of 204 signals, and testing with the remaining 36 signals.

The performance of the classification of the 4 emotional states is represented in TABLE IV. The analysis was done here on the whole EEG signal and not on the four waves taken separately (alpha, beta, delta and theta).

TABLE IV. PERFORMANCE OF CLASSIFICATION WITH NN

Number of neurons from the hidden layer	**State of joy [%]**	**State of anger [%]**	**Listening to Chopin's music [%]**	**Listening to Queen's music [%]**
5	91,67	94,44	94,44	97,22
10	100	100	100	100

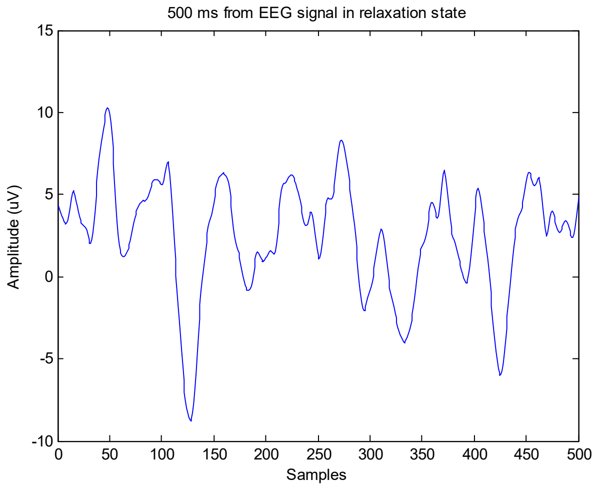

Fig. 5. A 500 ms portion of the EEG signal in the relaxed state.

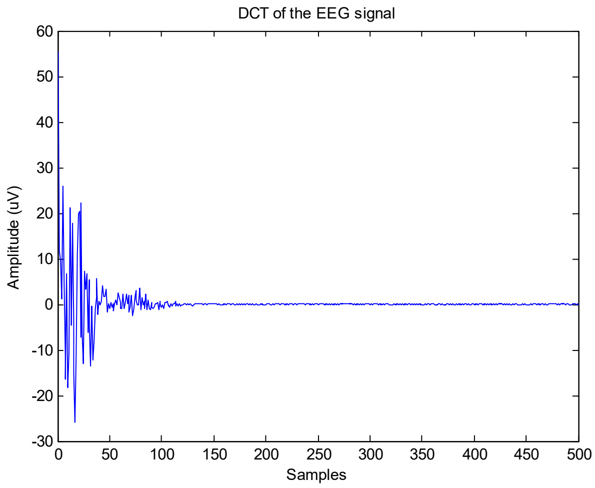

Fig. 6. DCT of the EEG signal represented in Fig. 5.

Fig. 7 represents the evolution of performance with the number of epochs in the 3 situations: network training, testing and validation, the minimum error of 0.15319% being obtained at iteration 14. Fig. 8 shows the confusion matrix indicating the percentage of the classification result in the two classes. Here the classes are given by the signal from the state of relaxation and the signal from the state of joy, and the hidden layer consists of 5 neurons. We notice that the sum of the percentages in the squares marked with green (also found in the blue square) represents the number of correct classifications. This number of 91.67% was moved to the corresponding position in TABLE IV.

Similar results are obtained if we compare two EEG signals obtained in different emotional states. If we compare the EEG signals generated in the states of joy and anger or the signals generated by listening to different musical pieces, we obtain similar results. Unfortunately, the data set is not enough to effectively train the neural network.

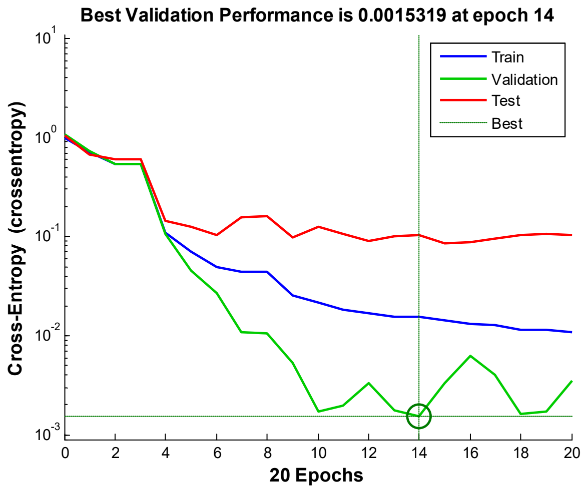

Fig. 7. Best validation performance of the network.

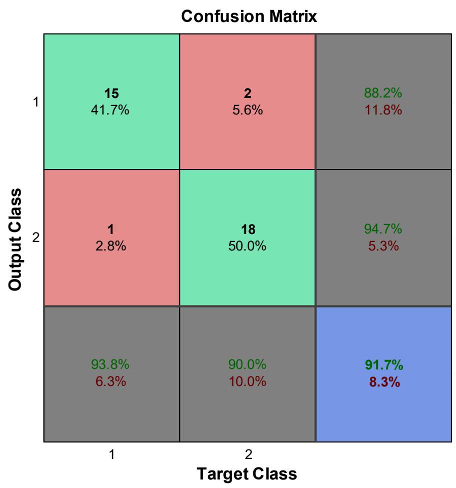

Fig. 8. Confusion matrix for the network with 5 neurons in the hidden layer.

V. Conclusion

In this paper we analyzed the possibility of detecting emotions using real EEG signals. We used several detection criteria, including the number of zero crossings, the averaging of samples over time, the averaging of the samples of the FFT and DCT transforms, as well as a neural network in which we used as input data the samples of the DCT transform. Classification of signals using the neural network provides very good results, even if the data set required to train the network is small.

Other methods used successfully in classifying EEG signals for emotion detection are mentioned in [11], being discussed SVMs, Naive Bayes, kNN, or AdaBoost.M1 algorithm. Of course, in the future other evolved neural networks may be considered, or different classification techniques based on fuzzy clustering [6].

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