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Emotion Recognition Based on EEG Signals

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***Abstract*—In this paper we propose some methods for analyzing EEG signals in order to recognize emotions, using the representation of signals on Poincaré plots and the calculation of the fractal dimension. 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, chaos, fractal dimension, nonlinear dynamics, emotion recognition

I. INTRODUCTION

Emotion Recognition and Affective Computing are now two growing research areas. In these fields various classification methods have been proposed, such as face expression, speech analysis, electrophysiological signals (ECG, EEG), skin conductance, and so on [1]. Nonlinear methods in the analysis of EEG signals have also been used in various applications to detect abnormal function of the brain like seizures, dementia, depression, autism, Alzheimer's disease, but also in healthy subjects, in perceptual processing, performance of cognitive tasks and different sleep stages [1].

A study that uses the chaotic features of electro-encephalogram in metabolic encephalopathy, where the brain functions are involved secondary to a metabolic disturbance, has been reported in [2]. Reference [3] analyzes the relation of EEG signal chaos characteristics with five kinds of consciousness activities (relaxation, mental multiplication, mental composition of a letter, visualizing a rotating 3-dimensional object, and visualizing numbers being written or erased on a blackboard). The authors use a phase space reconstructs technique from one-dimensional and multi-dimensional time series. Several links between EEG data processing and quantum mechanics are presented in [4]. Emotion recognition based on EEG features in movie clips has been studied in [5], and the effect of listening to music on EEG signals has been described in [6] and [7].

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 slow piece of music by Chopin and listening to a rock song by the band Queen. EEG signals were recorded using an MP36 Biopac Acquisition Unit that has four analog channels with A/D sampling resolution of 24 bits, maximum sample rate of 100,000 samples/s each channel, 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), with the sampling rate fixed at the value of 1,000 samples/s, during 60 seconds [8].

We show in the work that the EEG signal for a healthy subject has a chaotic behavior and not a random one and we suggest some possibilities to identify the signals generated in different emotional states. One of the proposed methods is the calculation of the fractal dimensions for different EEG signals, which was also done for the four frequency bands in the EEG signal, i.e. alpha, beta, theta, and delta waves.

The paper is organized as follows: section II describes the discrete-time logistic model and the representation of EEG signals on the Poincaré plot, section III presents a method used for calculating the fractal dimension for different EEG signals, and section IV contains the experimental results. Section V concludes the paper.

II. CHAOS IN EEG SIGNALS

The discrete-time logistic model is a system that evolves over time based on the discrete logistic equation:

$$X_{N+1} = r \cdot X_N \cdot (1 - X_N) \quad (1)$$

where X_{N+1} is the signal X at the moment of time N+1, and X_N is the signal X at the moment of time N. The value of the parameter r is very important for the system behavior. If its value is less than 3, then the system has a single point attractor or a stable equilibrium point. This equilibrium point becomes

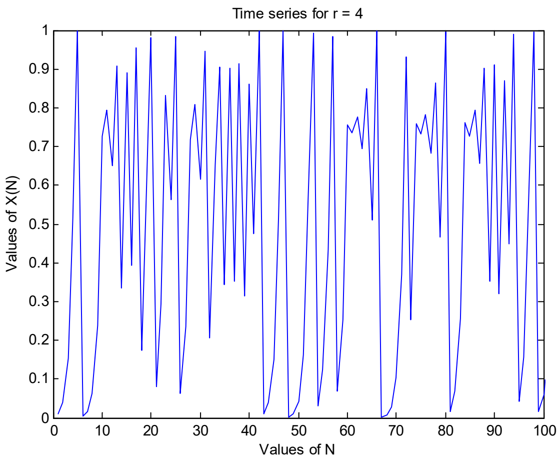

Fig. 1. Time series of the discrete logistic model with $r = 4$ and X_0=0.01.

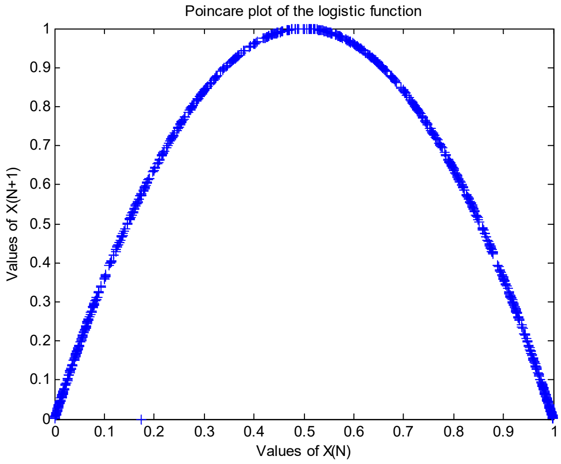

Fig. 2. Graph of the function $X_{N+1} = r \cdot X_N \cdot (1 - X_N)$ with r = 4.

unstable when $r > 3$. If $3 < r < 3.4$, then a simple 2-point periodic attractor arises and the final behavior of the system is an oscillation between two points. If we raise r further, the 2-point oscillation is lost and is replaced by a 4-point oscillation, then an 8-point oscillation, and so on. These kinds of bifurcations, called period-doubling bifurcations, occur faster and faster, until a limit point is reached and the system behavior becomes truly chaotic. If $r = 4$, the dynamics of the discrete logistic model are aperiodic, and the time series graph looks like in Fig.1. The state of the system can be any number between 0 and 1. The discrete logistic model is deterministic; there is no randomness in logistic equation given above ([9]).

In Fig. 1 we represented only 100 samples from the time series graph and in Fig. 2 on the Poincaré plot are represented all 1000 points. In the case of a chaotic system, that is the future is determined by the past, the points from the Poincaré plot lie exactly on the curve $X_{N+1} = 4 \cdot X_N \cdot (1 - X_N)$, like in Fig. 2, but they fill in that curve in what looks like a random manner. If the Poincaré plot has some simple shape, with the points placed on a curve, or on a single line, then the behavior is not random, but chaotic.

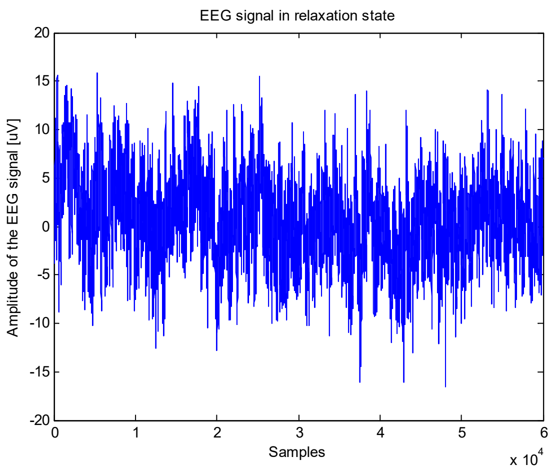

Fig. 3. EEG signal in relaxation state (60000 samples, that is 60 seconds).

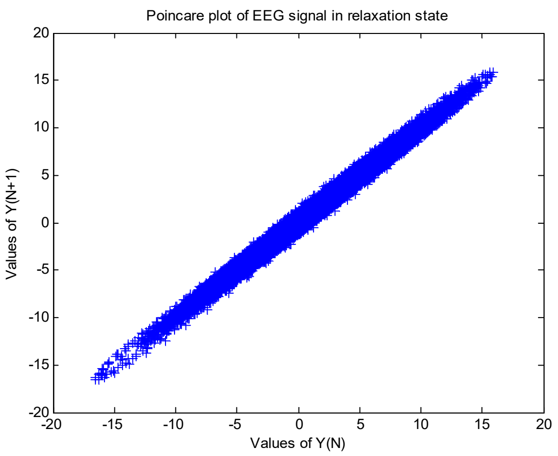

Fig. 4. Poincaré plot of EEG signal in relaxation state (60000 points).

In the case of a real EEG signal, as shown in Fig. 3, all 60000 points have been placed on the Poincaré plot represented in Fig. 4. EEG signal was denoted here with Y_N. As we can see, the points are not placed randomly, but rather on a line. This suggests that the EEG signal has a chaotic deterministic behaviour and this conclusion is supported also by other works, such as [9] and [10].

III. Fractal Dimension of EEG Signals

Reference [10] shows that EEG signal has a fractal structure. The author uses the Detrended Fluctuation Analysis (DFA) algorithm to determine whether the locally-detrended EEG signal contained long-range correlations, indicating fractal structure, or whether it was best characterized as a stochastic random-walk process. Fractal dimension calculated with this algorithm was 1.26.

In this paper fractal dimension is calculated using the box-counting dimension method, which is described in [11]. This concept is related to the self-similarity dimension: it gives the same numbers in many cases, but also different numbers in some others. We put the fractal structure that is analysed on a

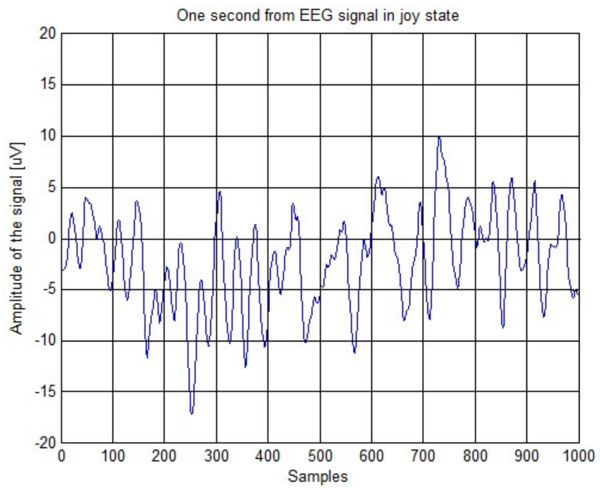

Fig. 5. One second from EEG signal in the state of joy, covered by 80 squares.

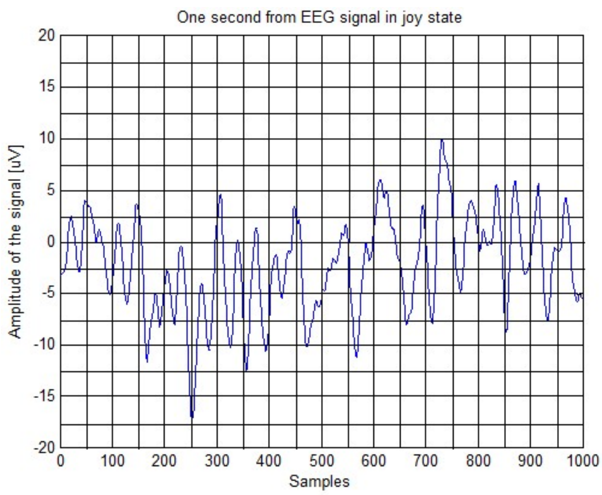

Fig. 6. One second from EEG signal in the state of joy, covered by 80 squares.

grid with mesh size s, and count the number of grid boxes which contain some of the structure. This gives a number, say N. Of course, this number will depend on the size. Therefore we write $N(s)$. Then s is changed to progressively smaller sizes and we count the corresponding numbers, $N(s)$. Then we plot the logarithms log(N(s)) versus log(1/s) and the slope of the line is the fractal dimension of the image.

In Fig. 5 we represented one second of EEG signal in the state of joy and the value of s is 100 samples on the x axes and 5 μV on the y axis. The image has 80 squares, and the signal occupies only 37 of them. In Fig. 6 the mesh size is reduced by a factor of 1/2. Now, the same signal is covered by 320 squares (each square has 50 samples on the x axes and 2.5 μV on the y axis), and the signal occupies 111 squares.

Now we can estimate the fractal dimension of this signal using the following equation:

$$d = \frac{\log 111 - \log 37}{\log 20 - \log 10} = \frac{\log(111/37)}{\log 2} = 1.584 \qquad (2)$$

Some advantages of box-counting dimension method are given in [11]: "The box-counting dimension is the one most used in measurements in all the sciences. The reason for its dominance lies in the easy and automatic computability by machine. It is straightforward to count boxes and to maintain statistics allowing dimension calculation. The program can be carried out for shapes with and without self-similarity. Moreover, the objects may be embedded in higher dimensional spaces. For example, when considering objects in common three-dimensional space, the boxes are not flat but real three-dimensional boxes with height, width, and depth."

IV. Experimental Results In Classification of Signals

We represented in Fig. 7 both EEG signals in the two different states, of relaxation and joy, on a single Poincaré plot. There are only 1000 points for each signal, which is one second of EEG signals. Green markers are generated by the relaxing EEG signal and the red markers belong to the EEG signal generated in the state of joy. Many of these markers overlap and for this reason separation into different classes is not easy. In Figs. 8, 9 and 10, the same representations were made for the alpha, beta and theta components of the EEG signals in the states of relaxation and joy, respecting the same convention regarding the colours used. All we can see from these graphs is that there are large differences in amplitudes between EEG signals and their components in the two states of relaxation and joy.

In order to compare these signals with each other, we calculated the average value of the samples during the 60 seconds in each case, using the following equation:

$$mean = \frac{1}{nr\_samples} \cdot \sum_{i=1}^{nr\_samples} |signal(i)| \qquad (3)$$

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 calculated results were listed 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.

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).

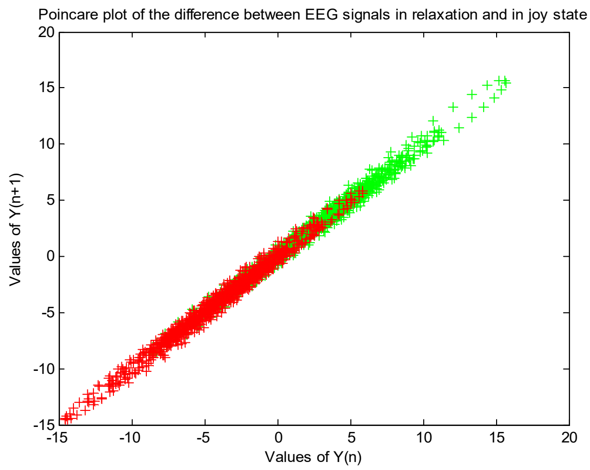

Fig. 7. The difference between EEG signals in relaxation and in joy.

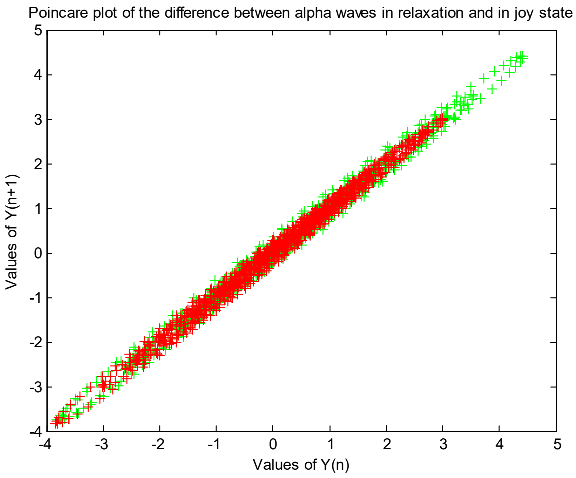

Fig. 8. The difference between alpha waves in relaxation and in joy.

TABLE I. 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

The results obtained by calculating the fractal dimensions using the box-counting dimension method are given in TABLE II. All values must be between 1 and 2. If they are equal to or less than 1, it means that small errors occur due to the chosen dimensions of the squares.

We notice here also a significant increase of the values of the fractal dimensions in the states of joy and anger (about 16%), especially through the contribution of alpha waves (about 40%). In the case of the musical piece by Chopin the increase is about 12%, especially through the contribution of beta waves (about 11%). Interestingly, in the case of the musical piece by Queen, there are no significant changes compared to the state of relaxation, and the results also agree with the data in TABLE I. An analysis of the different EEG seizures using the fractal dimension is made in [12], but their values are less significant, being between 1.3925 and 1.5652.

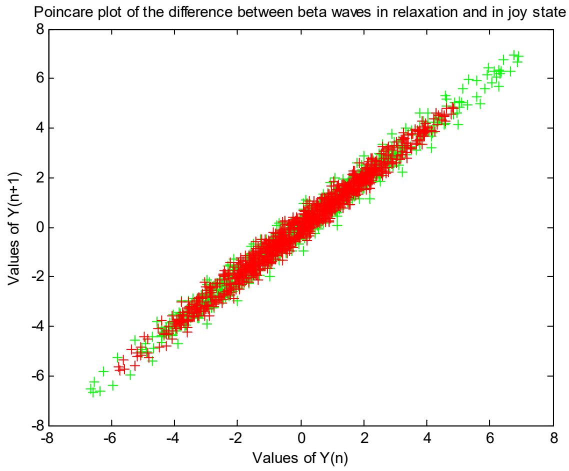

Fig. 9. The difference between beta waves in relaxation and in joy.

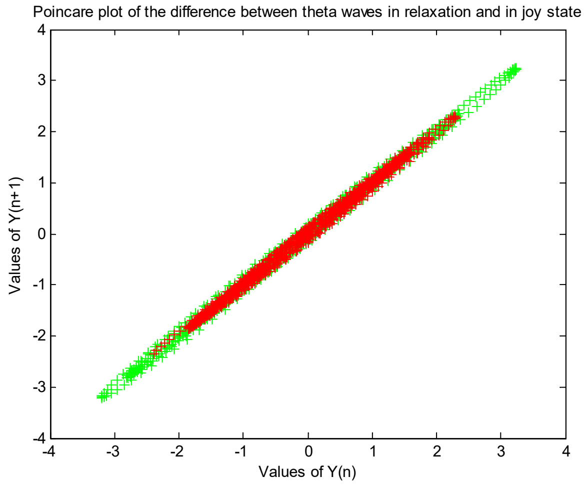

Fig. 10. The difference between theta waves in relaxation and in joy.

TABLE II. FRACTAL DIMENSIONS

State	EEG signal	Alpha wave	Beta wave	Theta wave	Delta wave
relaxation	1.359	1.035	1.490	1.035	1.000
joy	1.584	1.459	1.433	1.202	1.099
anger	1.473	1.398	1.517	1.293	1.293
Chopin	1.522	1.099	1.646	1.000	0.944
Queen	1.368	1.104	1.348	0.964	1.064

By comparison with the results obtained in the reference [12], we notice that the variation of fractal dimensions is larger in the case of emotions, especially if we analyze each component wave separately.

V. Conclusion

Using real EEG signals, collected in our laboratory, we showed on the Poincaré plots that the EEG signals are chaotic and not random. We used the mean of the amplitudes of the EEG signals and their waves (alpha, beta, delta and theta) to detect states that generate emotions. Then we adapted the calculation of the fractal dimension using the box-counting dimension method for EEG signals and showed that the fractal dimension can be used successfully in emotion recognition.

Future studies can be done by calculating the average energy of the samples in the signal or by comparing the samples resulting from transformations in the frequency domain (Fourier, Discrete Cosines Transform (DCT) etc.). Also, the use of Artificial Neural Networks (ANN) can be a very useful tool in classifying EEG signals.

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