Neural Networks for Chaotic Signal Processing: Application to the Electroencephalogram Analysis for Epilepsy Detection

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Abstract: *Many techniques were used in order to detect and to predict epileptic seizures on the basis of electroencephalograms. One of the approaches for the prediction of epileptic seizures is the use the chaos theory, namely determination largest Lyapunov's exponent or correlation dimension of scalp EEG signals. This paper presents the neural network technique for epilepsy detection. It is based on computing of largest Lyapunov's exponent. The results of experiments are discussed.*

***Keywords*:** Independent component analysis, neural network, Lyapunov's exponent, electroencephalography.

I. INTRODUCTION

Problem concerning the processing of an EEG data have existed for a very long time. Traditional methods of EEG analysis are based on linear mathematics. However, linearity is not good tool for investigation of complex and chaotic processes. In many real systems (e.g., chemical reactions, irregular heart beats, stock market, EEG patterns of brainwave activity, central nervous system, social behavior), a chaotic behavior has been observed, i.e., a complex, erratic, extremely input-sensitive behavior which cannot be easily understood. Chaos theory is nowadays widely studied and applied in various areas to describe, characterize, and possibly predict the system behavior when such kind of complexity occurs [1]. Therefore nonlinear signal processing is becoming a more and more tool for the study of complicated systems. The techniques of nonlinear signal processing are summarized in [2,3]. Much of nonlinear signal processing is based on an embedding theorem [4]. It guarantees that a full knowledge of the behavior a system is contained in the time series of any a one measurement and that a proxy for the full multivariate phase space can be constructed from the single time series. To apply the embedding theorem it is necessary to define embedding dimension and time delay. There exist several methods [2,3] for this (Lyapunov's exponents, fractal and correlation dimension, mutual information, etc). The chaotic behavior of a dynamical system can be described either by nonlinear mathematical equations or by experimental data. Unfortunately, often we do not know the nonlinear equations that describe the dynamical system. The problem consist therefore in identifying the chaotic behavior and building a model that captures the important properties of the unknown system by using only experimental data. In order to determine the main properties of our model, we can use the dynamic invariants (namely: correlation dimension, Lyapunov's exponents and Kolmogorov's entropy). However, in practice, the existing approaches for determination of Lyapunov's exponents from experimental data are characterized by computational complexity and may be performed using a large length of data [5]. But in many cases it is very problematic to reach for real data. Therefore the traditional approaches have been limited in their applicability to many real world chaotic data. One way to avoid this problem is to use neural networks approach for computing Lyapunov spectrum using an observable data [5].

The important application of the chaos theory is the processing of EEG data with purpose of the detection and prediction of epileptic seizures. Epilepsy is one of the most serious neurological disorders, affecting 1% of the population in the world. The analysis of the EEG signals has been the subject of many studies [6,7]. A rapidly growing number of studies deal with the applying of chaos theory to the detection and prediction of epileptic seizures. Some techniques based on the computing of the largest Lyapunov's exponents of the patient's electroencephalogram. In an epileptic's brain, the amount of chaos decreases and the maximum Lyapunov's exponent is decreased in the leading up to seizures [7]. Therefore it is very important to have robust methods of chaotic signal processing for automatic detection and prediction of abnormality in EEG data. This paper is oriented on applying Neural Networks to problem in the domain of chaotic time series processing with purpose of detection abnormal patterns in EEG.

The rest of the paper is organized as follows. Section 2 describes the ICA approach for EEG data preprocessing. Section 3 tackles the neural network approach to computing of largest Lyapunov's exponent. Section 4 presents the experimental results of applying neural network to epilepsy detection.

II. PREPROCESSING OF EEG DATA

As it is mentioned before the brain is very complex system. Electroencephalograms are recording of epileptic activity from neural currents within the brain. The EEG is used for monitoring the electrical activity of the human brain. It permits to understand the neurodynamic of the brain and to detect epileptic seizures.

The independent component analysis (ICA) is a powerful approach for artifacts (electrical activity of the heart, eye-blink and other muscle activity) and noise identification and removal from EEG data [8]. As a result we can extract the useful information for further processing. ICA is based on assumption of statistically independence of the signal sources. It is assumed also, that EEG data are linear mixing of signals from different sources. Let's assume that at time there are an n input unknown statistically independent sources $Si(t)$ $(i=1,2,\ldots,n)$ of signals. These signals present electric activity from the brain and artifacts. Due to linear combinations of unknown sources are obtained m mixed signals (Fig. 1).

$$X_j(t)=\sum_{i=1}^{n} S_i(t) w_{ij},$$

where $[w_{ij}]$, $i=\overline{1,n}$, $j=\overline{1,m}$ - unknown mixing matrix.

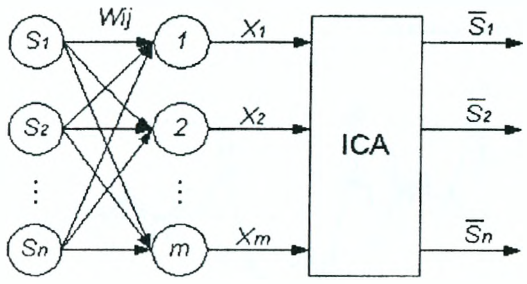


Fig. 1. Diagram of mixing and separating signals.

The goal of ICA is to estimate on the basis of mixing signals $X_j(t)$, $j=\overline{1,m}$ unknown sources of signals.

$$S_i(t)=\sum_{j=1}^{m} v_{ji} X_j(t).$$

It is performed by a linear transformation of the observed, sphered vector X by such a way, that the elements of the transformed vector are statistically independent. In many ICA algorithms maximizing the norm of the fourth-order cumulant, also called the kurtosis, or maximizing the negentropy are used for this purpose. As a result of ICA data processing we can extract and eliminate noise and artifacts.

III. A Neural Network for Estimation of Lyapunov's Highest Exponent

The use of neural networks for computing the highest Lyapunov's exponent and was presented in [5]; it relies on the evaluation of the divergence between two orbits at n step ahead by means of an iterative approach. The neural network for the highest Lyapunov's exponent is a multilayer network with $k \geq D-1$ input units (where D is the embedding dimension), p hidden units, and one output unit (Fig. 2).

This network allows us to reconstruct an attractor from an arbitrary initial point. As a result our network preserves a system dynamics. It means that for every point in the attractor we can take the nearest point, which is far from it at some distance, and then trace its trajectory.

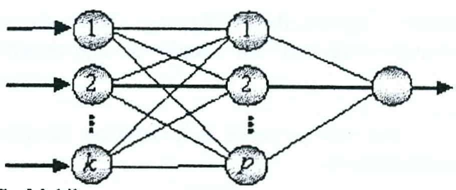


Fig. 2. The Multilayer perceptron for the highest Lyapunov's exponent.

In this case the algorithm of Lyapunov's highest exponent calculation from a small time series can be described in the following way [9-14]:

1. After the construction with the use of embedding parameter we train a forecasting neural network by sliding windows technique.
2. Let us take an arbitrary point $[x(t), x(t+\tau), \ldots, x(t+(D-2)\tau)]$ in the attractor from the training set and with the use of multi-step prediction and describe its trajectory $x(t+(D-1)\tau)$, $x(t+D\tau)$, ...
3. In the reconstructed phase space we take the nearest point $[x(t), x(t+\tau), \ldots, x(t+(D-2)\tau)+d_0]$, where $d_0 \approx 10^{-8}$ and predict its behavior $x'(t+(D-1)\tau)$, $x'(t+D\tau)$ with the use of a neural network.
4. Let's calculate
$\ln d_i = \ln\left|x'(t+(D-2+i)\tau)-x(t+(D-2+i)\tau)\right|, i=1,2,\ldots$
and take only such points, where we have $\ln d_i < 0$.
5. Plot a graph $\ln d_i$ versus $i\tau$.
6. Let's find a line of regression for taken points and estimate its slope, which is equal to the Lyapunov's highest exponent.

The given approach permits to estimate largest Lyapunov's exponent using a small data set.

IV. Results

For our research we used real EEG signals from web-site [15]. These sets of data are filtered from artifacts and noise. We made experiments on EEG signals that are characterized different epileptiform activities: single spikes or sharp waves, a sequence of spikes. Figure 3 shows a signal with one spike in the interval near 1.15-1.45 sec.

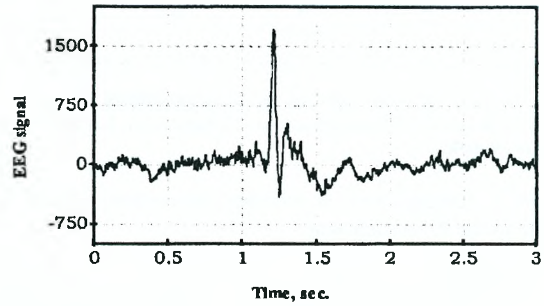


Fig. 3. The EEG signal with a single spike.

Such EEG signals permit us to ascertain epilepsy visually. We can analyze these signals and realize results check clearly. The raw data (EEG signals) represent text files contain a sample of the amplitude signal with rate 0.03 sec.

Lyapunov's exponent to serve as a criterion for detection epileptiform activity:

$$\begin{cases} \lambda > 0, \textit{ normal activity;} \\ \lambda \le 0, \textit{ epileptiform activity.} \end{cases}$$

The computation of Lyapunov's exponent is performed using predictive artificial neural network (ANN). We propose to apply multilayer perceptron (MLP) with one hidden layer. In the hidden layer and the output layer we use sigmoidal and linear activation function respectively. The EEG signal is employed as the MLP inputs.

At first, we compute embedding dimension m and time delay τ of ANN inputs (for the signal on figure 3: $m=7$, $\tau=4$). The defined MLP is trained with backpropagation algorithm. Then the Lyapunov exponent λ is evaluated in each point of the input data. In the result we have time-dependent deterministic series $\lambda(t)$:

$$\lambda(t) = (\lambda_1, \lambda_2, ..., \lambda_L),$$

where L is the size of a learning sample.

Epilepsy identification presents difficulties for us, when the criterion (4) is applied to series (5). We find out that series $\lambda(t)$ are characterized by amplitude instability. Problem solving is Lyapunov exponents averaging $\overline{\lambda}(t)$ in interval $n \approx 20 \pm 10$:

$$\overline{\lambda}_k = \frac{\lambda_{k-[n/2]} + \lambda_{k-[n/2]+1} + ... + \lambda_{k+[(n-1)/2]}}{n}.$$

Now we can detect epileptiform activity, because average readings clear from jumping in signal. However, low accuracy and false detection are present in average series by reason of miscalculation Lyapunov's exponents at the end of the learning sample. Figure 4 shows how the program composes the learning samples for ANN from the EEG signal.

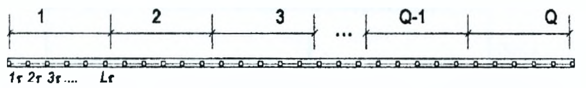


Fig. 4. Partition the EEG signal on the learning samples is one after another. Q is number of learning samples, τ is time delay, L is the size of a learning sample.

Figure 5 demonstrates a problem resolution, which is visible in the following way:

- Partition the EEG signal is executed with the learning samples overlap.
- ANN is trained on L-dimension learning samples, but Lyapunov's exponents is computed at the fist h items. The next learning sample is selected from $h+1$ data item.

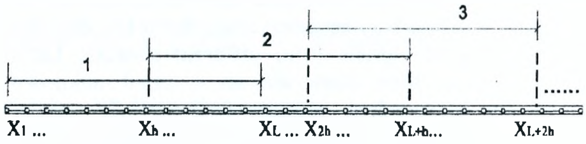
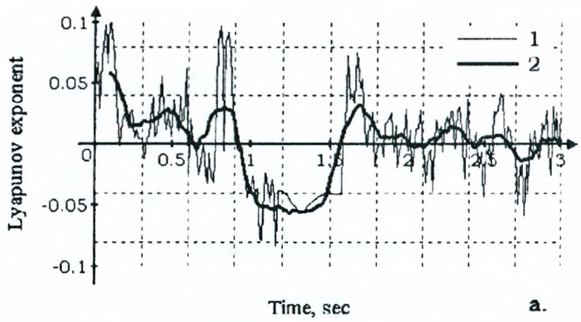
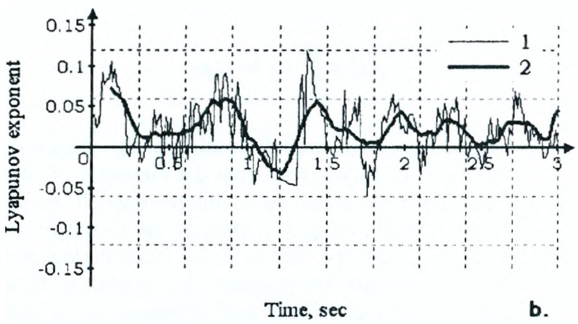


Fig. 5. The learning samples overlap. h is size of data for computing Lyapunov's exponents in each learning sample.

As is obvious from the foregoing, this proposal has some defect, which consists in decreased data-rate. Influencing factor is increase in the number of the learning samples. However, in this way program are saved from false detection of epileptiform activity, because recording area with estimated error don't use. Experimental results are showed on figures 6.



a.



b.

Fig. 6. Lyapunov's exponents are computed: *a)* at full length of the learning sample *b)* at the fist h items. 1 - time dependence $\lambda(t)$, 2- averaging time dependence $\overline{\lambda}(t)$.

Let's analyze the findings:

a) Lyapunov's exponents were computed at full length (30 items) of the learning sample. If series $\lambda(t)$ are considered, demonstrably, including many sudden changes it are characterized by amplitude instability. This instability provokes false detection of epilepsy. In consideration of series $\overline{\lambda}(t)$ we may well determine epileptiform activity and approximate interval of epileptic event 0.9-1.6 sec. However measure of inaccuracy (0.25 sec) is significant error.

b) Lyapunov's exponents were computed at the fist $h = 10$ items. Here we examine only series $\overline{\lambda}(t)$. Measure of inaccuracy is useful decrease (0.05 sec). Moreover false amplitude decays below the zero line are eliminated completely. In the result one epileptiform event is detect in interval 1.1-1.3 sec.

Experiments are also run on the EEG signal comprising a sequence of spikes. Similar results are found, which validate drawing conclusions. We accumulate findings in the table 1.

Table 1. The detection results of epileptiform activities.

No.	Epileptic events (time interval, sec)	Detection of epileptic events, where $h = L = 30$ (time interval t, sec)	Detection of epileptic events, where $h = 10$ (time interval t'', sec)	Measure of inaccuracy Δt', c	Measure of inaccuracy Δt'', c
1.	0,20 – 0,30	0,25 – 0,45	0,20 – 0,35	0,15	0,05
2.	0,50 – 0,60	0,45 – 0,55	0,50 – 0,60	0,05	0
3.	0,80 – 0,90	0,70 – 0,85	0,85 – 0,90	0,1	0,05
4.	1,10 – 1,20	0,90 – 1,20	1,05 – 1,20	0,2	0,05
5.	1,35 – 1,45	1,30 – 1,55	1,30 – 1,50	0,1	0,05
6.	1,60 – 1,70	1,65 – 1,85	1,65 – 1,75	0,15	0,05
7.	1,95 – 2,05	1,90 – 2,10	1,95 – 2,05	0,05	0
8.	-	2,15 – 2,25	-	-	-
9.	2,20 – 2,30	2,30 – 2,45	2,25 – 2,35	0,15	0,05
10.	2,55 – 2,65	2,55 – 2,70	2,55 – 2,65	0,05	0
Maximum inaccuracy:				0,2	0,05

V. Conclusion

In this paper we have addressed the key aspects of EEG data processing for epilepsy detection. It is based on using of ICA method and multilayer perceptron. The ICA approach is used for extraction and elimination noise and artifacts. The MLP is applied for largest Lyapunov's exponent computing. We proposed technique for avoiding false detection of epileptic activity. All epileptic events and their intervals of activity were found in tested EEG data. Measure of inaccuracy was 0.05 sec. Our results are limited of EEG data records. Therefore the next step is to test proposed approach using real EEG data from hospital.

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