# Neural Networks and Largest Lyapunov Exponent for Automatic Epileptic Seizure Detection in EEGs

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***Abstract:*** *We report a novel method for epileptic seizure detection that is reliant on the maximal short-term Lyapunov exponent (STLmax). The proposed approach is based on automatic segmentation of the EEG into epochs that correspond to epileptic and non-epileptic activity. The STLmax is then computed from both categories of EEG signal and used for classification of epileptic and non-epileptic EEG segments throughout the recording. Neural network techniques are proposed both for segmentation of EEG signals and computation of STLmax. The data set from hospital have been used for experiments performing. Furthermore, the publicly available data were used for experiments. The main advantages of presented neural technique is its ability to rapidly detect the small EEG time segments as epileptic or non-epileptic activity, training without desired data set about epileptic and non-epileptic activity in EEG signals.*

***Keywords*****:** Multilayer perceptron, chaos, largest Lyapunov exponent, electroencephalogram, epileptic seizure.

## 1. INTRODUCTION

The scalp EEG is the most widely-used diagnostic tool in epilepsy, a common neurological disorder that affects approximately 1% of the world's population [1]. Seizure detection, as well as detection of epileptiform interictal activity, is an essential part of day-to-day management of patients with epilepsy. Notably, although most EEG data are now digital, and numerous protocols for automated seizure detection are available [1-15], the EEG is still largely analyzed by visual inspection. Here, we present a novel method for automated detection of seizure and epileptic interictal discharge based on the maximal short-term Lyapunov exponent (STLmax), a measure of dynamic system instability which has been extensively used in EEG analysis [2,16]

Previous studies show nonstationarity and chaotic nature of EEG data, and thus justify a measure of entropy such the STLmax [2, 7-9]. There exists clear difference in dynamical properties of the EEG signals in non-epileptic and epileptic state. Epileptic seizures are characterized by synchronized neuronal firing which reduces EEG complexity. It is known that the STLmaxis reduced during epileptic activity, and for this reason the STLmax calculation has been proposed as a component of seizure detection protocols [2, 4, 7-9]. However, the conventional approaches for computing of the STLmax exponent are very sensitive to the volume of data and computationally intensive [17]. In order to estimate the STLmax for EEG data, a modified Wolf algorithm [16] are used in [2]. However, the existing approaches have the following drawbacks: unreliable for small data-set size and computationally intensive. Therefore, the many authors use for computing of STLmax long EEG segments with time length of 10,24 s [18-20]. One limitation of previous study is that these don't permit to detect exactly the small EEG segments with epileptic and non-epileptic activity.

Seizure detection by machine learning protocols is often accomplished in two stages: (1) feature selection and (2) event classification [4, 10-15] However, present approaches to feature selection have a disadvantage in their inability to select time segments with epileptic activity in EEG and the requirement for neural network training on desired data set, which necessitates some amount of non-automated EEG analysis in order to identify representative epileptic and non-epileptic EEG segments to be used as templates for the automated algorithm [1,3-6,10-15].

The basic idea of this paper is to detect exactly the EEG segments of different duration with epileptic and non-epileptic activity. It permits to identify pathological activity in remission state and to detect paroxysmal activity in preictal period. We propose neural networks technique both for time segmentation of EEG signals and computation of the STLmax. As mentioned, the epileptic seizure is characterized an STLmax decrease, and we propose to exploit the change of the STLmax over time as a criterion of epileptic seizure in EEG segments.

Neural networks techniques permit to reduce the diagnostic time and the number of misdiagnosis, as well as to assist the doctor in making decision. The clinical data from the 5th City Hospital (Minsk, Belarus) have been collected for testing of the proposed approach. Furthermore the publicly available data were used for experiments [21]. The efficiency of epileptic seizure detection is illustrated by the experimental results.

The paper is organized as follows. The dataset used in this work and proposed methodology is given in Section 2. In Section 3 the experimental results are described. Finally, discussions are given in the last section.

## 2. DATABASE

In this research we have used two datasets for proposed approach testing. The first one described in [22] and publicly available from [21]. The second one have been taken from 5thCityHospital in Minsk (Belarus). Let's consider these databases.

The complete dataset [22] includes five subsets (denotes A, B, C, D and E), each containing 100 single-channels EEG signals of 23,6s duration with sample frequency of 173,6 Hz. Set A and B have been taken from surface EEG recordings of five healthy volunteers with eyes open (set A) and closed (set B), using international 10-20 electrode placement scheme. Set C and D consist of inter-ictal recordings from five epileptic patients. Electrodes were placed on epileptic zone for set C and on the hippocampal formation of the opposite hemisphere of the brain for set D. Thus sets C and D contains activity of epileptic patients measured during seizure free intervals. Set E includes seizure activity, selected from all recording sites exhibiting ictal activity.

The next database was collected from the 5th City Clinical Hospital (Minsk, Belarus) for 20 adult patients with epileptic activity. During long time was performed patient's examination, using 16-channel registration of EEG. The EEG signals have been registered with the sampling rate of 250 samples per second. The duration of one registration was approximately 30 min. 50 registrations were realized for each patient. As a result of processing these EEG data, the EEG database was created, which represents the set of 48 registrations of 16-channel EEG, selected from eight adult epileptic patients during 8 seconds for each registration. It may be noted, that each signal in EEG was presented as time series of 2000 points. Thus the EEG database contains 48x16=768 EEG time series. The total number of epileptic events in these EEG signals is 102. The epileptic events were selected due the long time examination of patients. We should note that practically impossible to indicate the seizure event in these EEG signals even for high quality the neurologist experts. Our goal is to detect in EEG signals the segments with epileptic and non-epileptic activity.

## 3. THE SYSTEM DESCRIPTION

In this section the neural network diagnostic system for epileptic seizure detection using EEG data is described. As a diagnostic criterion the value of the STLmax is used, which is decreased during seizures. The STLmax characterizes sensitivity to initial conditions [16, 17]. It is statistical measure of divergence between two orbits starting from slightly different initial conditions. The neural network diagnostic system is shown in Figure 1. It consists of different units, which are combined in diagnostic system. One can see from Figure 1 the system inputs are multi-channel EEG patient data of patient. These data can be interpreted as an observation of chaotic dynamical system generating electrophysiological waves. EEG data recorded from scalp electrodes contain different artifacts and consist of various signals combination. Therefore, in the first stage (preprocessing) the independent component analysis (ICA) is used for artifacts removal and extraction of the independent sources from their mixtures [23]. ICA separates the independent sources from their mixtures by measuring non-Gaussian. As a result, we can get independent and clean EEG data without artifacts and noises.

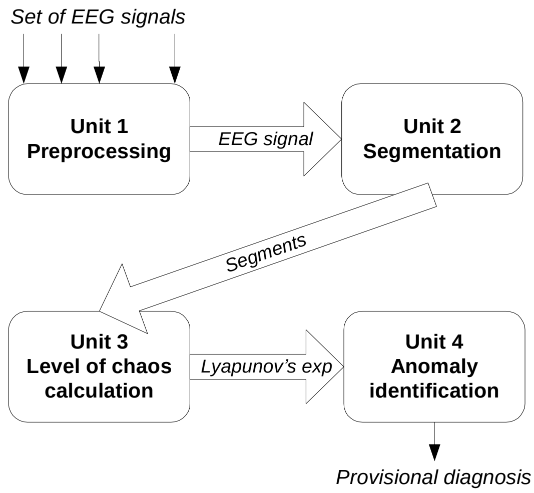


**Fig. 1 – There is neural network system for epileptic activity detection. The set of EEG signals is used as input data for the system.**

In the second stage every EEG signal is divided into quasi-stationary segments, using adaptive segmentation algorithm. The segment is called quasi-stationary when its behavior does not change under a time shift. The multilayer neural network (MLP) is used for adaptive segmentation of EEG signal. The multilayer perceptron consist of 7 units input layer, 5 units hidden layer and 1 output unit (Fig. 2). The minimal initial length of EEG segment is 70 points and is changed during adaptive segmentation. The computation of the STLmax for every extracted segment is performed on the third stage (level of chaos calculating). As a result, the sequence of the STLmax for every EEG signal is obtained:

$$\lambda(t) = (\lambda_1, \lambda_2, .. \lambda_p), \qquad (1)$$

where p – the number of selected segments.

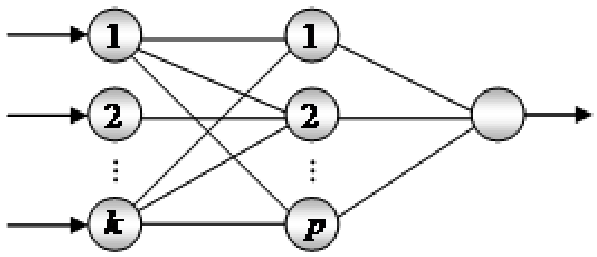


**Fig. 2 – Predicting neural network includes three layers. Each layer consists of k, p and one neurons.**

As a result, the sequences of segments with different values of the STLmax are obtained. If the different segments have the same value of the STLmax they are combined into a one segment.

Finally, the epileptic seizure identification is performed in accordance with the following test:

$$\begin{cases} \lambda > 0, normal\ \ activity; \\ \lambda \le 0,\ epileptic\ \ activity. \end{cases} \qquad (2)$$

As a result, we obtain the segments in EEG signals with epileptic and non-epileptic activity.

The algorithm of the dividing initial EEG signal into elementary intervals by the neural network approach is as follows:

1) EEG signal is divided preliminary into the short segments of the length of N points (N=70). The start point of the sliding window is t = 1.

2) The training samples are formed: {x(t), x(t+1),… x(t+N-1)}.

3) Multilayer perceptron is trained by means of sliding window approach.

4) The perceptron begins to predict the points of segment. As a result the following points are obtained: {x’(t+N), x’(t+N+1), x’(t+N+2), …}. The data prediction is ended when expression (3) is fulfilled.

$$|x'(i) - x(i)| > \Delta x_{\max} \quad (3)$$

Where i = t+N, t+N+1,…, Δxmax=0,1 is a appropriate error of the forecasting.

5) If i = t + N (expression (4) is fulfilled) then i is a point of the segment border and the next training data set are formed beginning from t= i. Otherwise the segment border moves on the number of the predicted points, i.e. t = i – N.

6) The procedure is continued, when t < m – N, where m is common length of time series.

After fulfillment of this algorithm we can get the set of different segments and multilayer perceptrons tuned on corresponding segments. It should be noted that we use for calculation of the STLmax the multilayer neural networks, received at the segmentation stage. As a result, the sequences of segments with different values of the STLmax are obtained. If the different segments have the same value of the STLmax exponent they are combined into a one segment.

## 4. EXPERIMENTAL RESULTS

In our research we used sets (A-E) of the EEG signals [21, 22]. There are 100 EEG segments in each set. Each EEG segment contains 4096 consecutive amplitude points; its duration is 23.6 seconds with sampling 173.61 Hz. We made experiments on the EEG signals that are characterized pathological (epileptic) and normal activities. Sets A and B consist signals recorded from healthy patients with eyes open (A) and eyes closed (B), respectively. Set C and set D includes EEG fragments during seizure-free intervals that were recorded from within the epileptogenic zone (C), and from the hippocampal formation of the opposite hemisphere of the brain (D). Set E contained activity during epileptic seizure.

All sets were used in experiment. Signals were classified on two classes: first class consisted signals with epileptic activity detected with using our system, second class included signals with only non-epileptic activity.

In the Table 1 the experimental results of classification are presented.

**Table 1. Classification results for sets A-E. Each set consists of 100 EEG signals.**

| Set | Class 1: epileptic activity | Class 2: normal activity |
|---|---|---|
| A | 0 | 100 |
| B | 0 | 100 |
| C | 6 | 94 |
| D | 32 | 68 |
| E | 92 | 8 |

It is significant, that there are no false detections of epileptic activity in sets A and B (see example in the Figure 4 a). In surgical treatment it is necessary to find the epileptic zone (the source of epileptic seizures). It is interesting, that 6 % epileptic activity detections in the set C were only single detections (only one segment with epileptic activity in each signal is detected). Example of the single detection presented in the Figure 4 b. When sets C and E were analyzed system had multiple detections in the signals in most cases (Figure 4 c). Figures 4 b and 4 c clearly show that the system can not only detect the presence of epileptic activity, but also to allocate the segments in which it is contained.

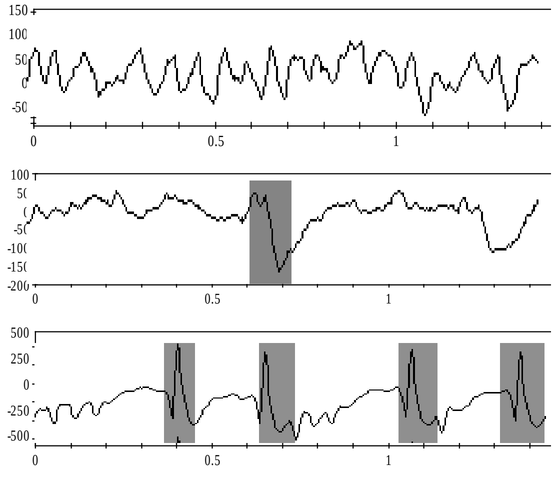


**Figure 4. Representative EEG signal fragments (sets A, C and E) analyzing. a) The fragment from set A hasn’t epileptic activity detection. b) The fragment from set C has one segment with epileptic activity (gray color). c) Four segments with epileptic activity (gray color) are detected in the fragment from set E.**

The next experiment is made with use EEG data given by the 5th City Clinical Hospital (Minsk, Belarus). The data represent set of 21 registrations of 16-channel EEG. EEG data was recorded from eight adult patients during 8 seconds for each registration. In the result of EEG data digitalization with frequency 250 Hz each signal in EEG was presented as time series of 2000 points. Total number of EEG signals is 336. In comparison with previous database these data contain different artifacts. As it was mentioned early for removing artifacts from EEG records we use independent component analysis (ICA), which can detect independent source signals from linear mixtures. All records of one registration are divided into six sets. The number of sets is selected by experimentally way according to the number of signals in the set for the correct filter, and to location of the electrodes.

Then each set of EEG signal is processed by ICA module. As a result, we have obtained six clean without artifacts EEG signals. After that the segmentation of each obtained EEG signals is performed. As a result, we detected 4364 segments from EEG signals of all registration (6x48=288). The results of classification all selected segment in the EEG data by the designed system are summarized in the Table 2.

**Table 2. Epileptic activity classification using database from hospital for 8 patients.**

| Real state | Number of all segments | Classification results | |
|---|---|---|---|
| | | Class 1: epileptic activity | Class 2: normal activity |
| Epileptic segments | 102 | 95 | 7 |
| Normal segments | 4262 | 12 | 4250 |

We can see that our system correctly detects 95 segments with epileptic activity from total number of 102 segments.

The test performance of the presented approach can be defined by the computation of sensitivity, specificity and total classification accuracy. The values of these statistical parameters calculated on the base of Tables 1 (sets A, B and E) and 2 are presented in Table 3.

**Table 3. Performance comparison on two dataset**

| Statistical parameters | Values for sets A, B, E | Values for clinical data |
|---|---|---|
| Specificity | 100,0 % | 99,7 % |
| Sensitivity | 92,0 % | 93,1 % |
| Total classification accuracy | 96,0 % | 99,6 % |

The results show that the presented in the paper methodology of EEG analysis are very specifically (99.7 %), it means that there are small counts of false epileptic activity detection. It is important because a misdiagnosis can have serious consequences. The value of the sensitivity means that the system in 93.1 % cases has right epileptic activity detection in real EEG data. The total accuracy of the segments classification in two classes (non-epileptic activity and epileptic activity) is equal 99.6 %.

## 4. CONCLUSION

In this paper the novel method for epileptic seizure detection using EEG waveforms have been addressed. The proposed approach is based on selection of the different time segments in EEG signals with epileptic and non-epileptic activity. The value of the STLmax is used for classification of epileptic and non-epileptic segments in EEG data. The neural network techniques are proposed both for segmentation of EEG signals and computation of STLmax. The proposed approach uses the same neural networks both for time segment selection and for STLmax computation in each segment using small data sets and faster in comparison conventional approach. This allows both for reducing the computationally complexity and for limit the observation time.

The data set from hospital have been used for experiments performing. The main advantages of presented neural technique is the ability to select in EEG small time segments with epileptic and normal activity, training without desired data set about epileptic and non-epileptic activity, the ability to assist the doctor in making decision and to visualize the zones (segments) of epileptic and non-epileptic activity in EEG signals using two-dimensional map [24–26]. Thus the proposed method has:

- high accuracy of segments classification for epileptic and non-epileptic activity;
- automatic detection of epileptic activity in the EEG;
- classification without prior training on the special desired data set;
- the ability to detect seizure activity of different shapes and duration;
- resistance to noise in the signals of the EEG.

It permits to detect exactly the EEG segments of different duration with epileptic and non-epileptic activity, to identify pathological activity in remission state and to detect paroxysmal activity in preictal period.

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