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AUTOMATED DIAGNOSTIC SYSTEM DEVELOPED FOR EEG SIGNALS USING LYAPUNOV EXPONENTS

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Abstract: In this study, a new approach based on the consideration that electroencephalogram (EEG) signals are chaotic signals was presented for automated diagnosis of electroencephalographic changes. This consideration was tested successfully using the nonlinear dynamics tools, like the computation of Lyapunov exponents. Multilayer perceptron neural network (MLPNN) architectures were formulated and used as basis for detection of electroencephalographic changes. Three types of EEG signals (EEG signals recorded from healthy volunteers with eyes open, epilepsy patients in the epileptogenic zone during a seizure-free interval, and epilepsy patients during epileptic seizures) were classified. The computed Lyapunov exponents of the EEG signals were used as inputs of the MLPNNs trained with backpropagation, delta-bar-delta, extended delta-bar-delta, quick propagation, and Levenberg-Marquardt algorithms. The performances of the MLPNN classifiers were evaluated in terms of training performance and classification accuracies. The results confirmed that the proposed MLPNN trained with the Levenberg-Marquardt algorithm has potential in detecting the electroencephalographic changes

Keywords: Electroencephalogram (EEG) signals, Chaotic signal, Lyapunov exponents, Multilayer perceptron

1. INTRODUCTION

The electroencephalogram (EEG) is a complex and aperiodic time series which is a sum over a very large number of neuronal membrane potentials. Despite rapid advances of neuro-imaging techniques EEG recordings continue to play an important role in both, diagnosis of neurological diseases and understanding psychophysiological processes. In order to extract relevant information from recordings of brain electrical activity a variety of computerized analysis methods have been developed. Most methods are based on the assumption that the EEG is generated by a highly complex linear system, resulting in characteristic signal features like nonstationary or unpredictability [1]. Much research with nonlinear methods revealed that the EEG is generated by a chaotic neural process of low dimension [2-4]. According to these reports, the EEG has a finite noninteger correlation dimension and a positive Lyapunov exponent. Furthermore, the distinct states of brain activity had different chaotic dynamics quantified by nonlinear invariant measures such as correlation dimensions and Lyapunov exponents [2-4]. In the present study, the computation of Lyapunov exponents was the basis for the automatic detection of electroencephalographic changes. More specifically, the EEG signals were modelled using multilayer perceptron neural networks (MLPNNs) trained with five different training algorithms. The computed Lyapunov exponents defining the behavior of the EEG signals were used as inputs of the MLPNNs.

2. MATERIALS AND METHOD

Decision making was performed in two stages: feature extraction by computing Lyapunov exponents (128 Lyapunov exponents selected as neural network inputs) and classification using the MLPNNs trained with the backpropagation (BP), delta-bar-delta (DBD), extended delta-bar-delta (EDBD), quick propagation (QP), and Levenberg-Marquardt algorithms. We used the data described in reference [5], which is publicly available. The MLPNNs were trained, cross validated and tested with the computed Lyapunov exponents of the EEG signals (set A - EEG signals recorded from healthy volunteers with eyes open, set D - EEG signals recorded from epilepsy patients in the epileptogenic zone during a seizure-free interval, and set E - EEG signals recorded from epilepsy patients during epileptic seizures).

Lyapunov exponents are a quantitative measure for distinguishing among the various types of orbits based upon their sensitive dependence on the initial conditions, and are used to determine the stability of any steady-state behavior, including chaotic solutions. The reason why chaotic systems show aperiodic dynamics is that phase space trajectories that have nearly identical initial states will separate from each other at an exponentially increasing rate captured by the so-called Lyapunov exponent [6-9]. This is defined as follows. Consider two (usually the nearest) neighboring points in phase space at time 0 and at time t, distances of the points in the i-th direction being $\|\delta x_i(0)\|$ and $\|\delta x_i(t)\|$, respectively. The Lyapunov exponent is then defined by the average growth rate λ_i of the initial distance,

$$\frac{\|\delta x_i(t)\|}{\|\delta x_i(0)\|} = 2^{\lambda_i t} (t \to \infty)$$

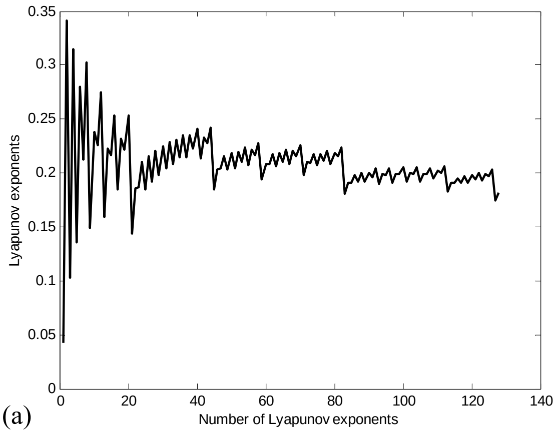
or

$$\lambda_i = \lim_{t\to\infty} \frac{1}{t} \log_2 \frac{\|\delta x_i(t)\|}{\|\delta x_i(0)\|}$$

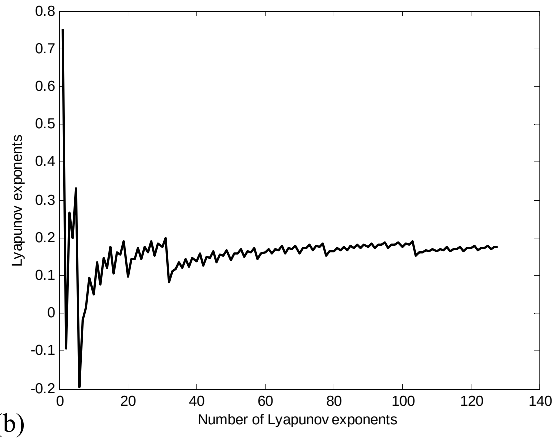
The existence of a positive Lyapunov exponent indicates chaos [6-9]. This shows that any neighboring points with infinitesimal differences at the initial state abruptly separate from each other in the i-th direction. In other words, even if the initial states are close, the final states are much different. This phenomenon is sometimes called sensitive dependence on initial conditions.

3. RESULTS AND DISCUSSION

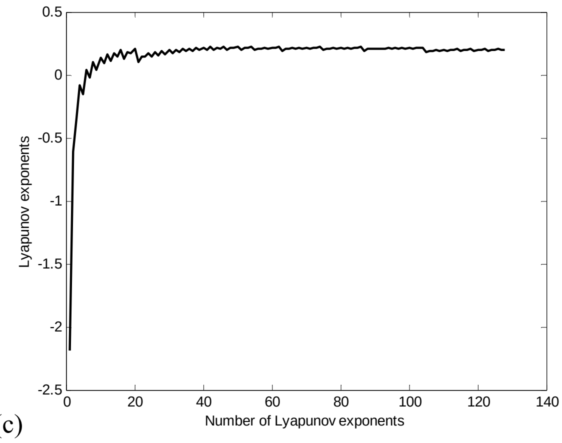
A rectangular window, which was formed by 256 discrete data, was selected so that it contained a single EEG segment. For the three diagnostic classes (set A - EEG signals recorded from healthy volunteers with eyes open, set D - EEG signals recorded from epilepsy patients in the epileptogenic zone during a seizure-free interval, and set E - EEG signals recorded from epilepsy patients during epileptic seizures) training and test sets were formed by 1200 vectors (400 vectors from each class) of 128 dimensions (Lyapunov exponents). In the present study, the technique used in the computation of Lyapunov exponents was related with the Jacobi-based algorithms. The Lyapunov exponents of the typical segment of EEG signals (set A - EEG signals recorded from healthy volunteers with eyes open, set D - EEG signals recorded from epilepsy patients in the epileptogenic zone during a seizure-free interval, and set E - EEG signals recorded from epilepsy patients during epileptic seizures) are given in Figures 1(a)-(c), respec-



(a)



(b)



(c)

Figure 1. Lyapunov exponents of the EEG segments (a) set A (EEG signals recorded from healthy volunteers with eyes open), (b) set D (EEG signals recorded from epilepsy patients in the epileptogenic zone during a seizure-free interval), (c) set E (EEG signals recorded from epilepsy patients during epileptic seizures)

tively. It can be noted that the Lyapunov exponents of the three types of EEG signals are different from each other. From Figure 1(a) one can see that all the Lyapunov exponents are positive, which confirm the chaotic nature of the EEG signals recorded from healthy volunteers with eyes open. As it is seen from Figures 1(b) and 1(c) there are positive Lyapunov exponents, which confirm the chaotic nature of the EEG signals recorded from epilepsy patients in the epileptogenic zone during a seizure-free interval, and epilepsy patients during epileptic seizures. As it is seen from Figures 1(a)-(c) there are positive Lyapunov exponents, which confirm the chaotic nature of the EEG signals.

In the present study, after several trials it was seen that two hidden layered network achieved the task in high accuracy. The most suitable network configuration found was 10 neurons for each hidden layer. In the hidden layers and the output layer, sigmoidal function was used, which introduced two important properties. First, the sigmoid is nonlinear, allowing the network to perform complex mappings of input to output vector spaces, and secondly it is continuous and differentiable, which allows the gradient of the error to be used in updating the weights. The MLPNNs were trained by using the BP, DBD, EDBD, QP, and Levenberg-Marquardt algorithms. For the Levenberg-Marquardt algorithm, the Marquardt parameter (γ) was set to 0.01. The MLPNNs were implemented by using the MATLAB software package (MATLAB version 7.0 with neural networks toolbox). The adequate functioning of ANN depends on the sizes of the training set and test set. The 600 vectors (200 vectors from each class) were used for training and the 600 vectors (200 vectors from each class) were used for testing. A practical way to find a point of better generalization is to use a small percentage (around 20%) of the training set for cross validation. For obtaining a better network generalization 120 vectors (40 vectors from each class) of training set, which were selected randomly, were used as cross validation set.

In training, a representative training set with examples was presented iteratively to the MLPNNs and the output activations were calculated using the MLPNNs weights. An error term, based on the difference between the output of MLPNNs and desired output, was then propagated back through the MLPNNs to calculate changes of the interconnection weights. The square difference between the output of MLPNNs and the desired output over training iterations was plotted for observing how well the MLPNNs were trained. The curve of the mean square error (MSE) versus iteration is the training curve. The values of minimum MSE and final MSE of the MLPNNs trained with five different training algorithms during training and cross validation are

Table 1.

The values of minimum and final MSE during training and cross validation

MLPNN trained with different algorithms	Number of epochs		Minimum MSE	
	Training	Cross validation	Training	Cross validation
BP	5800	5800	0.005491	0.006119
DBD	4000	4000	0.001662	0.001704
EDBD	2800	2800	0.000761	0.000823
QP	1700	1700	0.000345	0.000457
Levenberg-Marquardt	800	800	0.000117	0.000226

Table 2.

The values of statistical parameters

MLPNN trained with different algorithms	Statistical parameters (%)			
	Specificity (healthy segments)	Sensitivity (seizure free epileptogenic zone segments)	Sensitivity (epileptic seizure segments)	Total Classification Accuracy
BP	87.50	88.00	87.00	87.50
DBD	90.00	90.50	89.50	90.00
EDBD	90.50	91.00	91.00	90.83
QP	92.50	92.00	91.50	92.00
Levenberg-Marquardt	95.00	95.50	94.50	95.00

given in Table 1. As it is seen from Table 1, MSE curve of the MLPNN trained with the Levenberg-Marquardt algorithm is converging to a small constant approximately zero in 800 epochs and the BP, DBD, EDBD, QP algorithms have poor convergence rates comparing with the Levenberg-Marquardt algorithm.

The values of the statistical parameters indicating classification accuracies are given in Table 2. As it is seen from Table 2, the MLPNN trained with the Levenberg-Marquardt algorithm classified healthy segments, seizure free epileptogenic zone segments and epileptic seizure segments with the accuracy of 95.00%, 95.50% and 94.50%, respectively. The healthy segments, seizure free epileptogenic zone segments and epileptic seizure segments were classified with the accuracy of 95.00%. According to Table 2, the correct classification rates of the MLPNN trained with the Levenberg-Marquardt algorithm for healthy segments, seizure free epileptogenic zone segments and epileptic seizure segments are higher than that of the other MLPNNs.

4. CONCLUSION

This paper presented a new application for automated diagnosis of electroencephalographic changes using Lyapunov exponents. Toward achieving this aim, the EEG signals were considered as chaotic signals and this consideration was tested successfully by the computation of Lyapunov exponents. This was the basis for the automated diagnosis of electroencephalographic changes. More specifically, the EEG signals were modelled using the MLPNNs. The MLPNNs trained with the BP, DBD, EDBD, QP, and Levenberg-Marquardt algorithms were used to detect electroencephalographic changes. The MLPNNs were trained, cross validated and tested with the computed Lyapunov exponents of the EEG signals recorded from healthy volunteers with eyes open, epilepsy patients in the epileptogenic zone during a seizure-free interval, and epilepsy patients during epileptic seizures. The classification results and the values of statistical parameters were used for evaluating the classifiers. The classifications of the healthy segments, seizure free epileptogenic zone segments and epileptic seizure segments, performed by the MLPNN trained with the Levenberg-Marquardt algorithm, were done with the accuracy of 95.00%. We therefore have concluded that the proposed classifier trained with the Levenberg-Marquardt algorithm can be used in detecting electroencephalographic changes.

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