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Statistics over Lyapunov Exponents for Feature Extraction: Electroencephalographic Changes Detection Case

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Abstract – 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. This paper presented the usage of statistics over the set of the Lyapunov exponents in order to reduce the dimensionality of the extracted feature vectors. Since classification is more accurate when the pattern is simplified through representation by important features, feature extraction and selection play an important role in classifying systems such as neural networks. 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 selected Lyapunov exponents of the EEG signals were used as inputs of the MLPNN trained with Levenberg-Marquardt algorithm. The classification results confirmed that the proposed MLPNN has potential in detecting the electroencephalographic changes.

Keywords – Chaotic signal, Electroencephalogram (EEG) signals, Feature extraction/selection, Lyapunov exponents

I. INTRODUCTION

The electroencephalogram (EEG) signals reflect the electrical activity of the brain. The study of the brain electrical activity, through the electroencephalographic records, is one of the most important tools for the diagnosis of neurological diseases [1], [2]. The traditional analysis relies, mainly, on the detection of spectral power changes, supervised by the visual inspection of the physician: different frequency bands are considered, and the corresponding spectral powers are computed, whose changes are related to both functions and disfunctions of the central nervous system [3], [4]. In many studies, the underlying systems generating the observed EEG signals are believed to be nonlinear or consisting of subsystems in which nonlinear mechanisms play an important role. Even when they are analyzed from healthy individuals, they manifest chaos in the nervous system [5], [6]. Linear modeling techniques, though they allow us to deal with simplified problems, can represent the underlying system only partially, without taking into account the nonlinear contribution. Even though fairly good results have been obtained using linear modeling techniques, they seem to provide only a limited amount of information about the signal because they ignore the underlying nonlinear signal dynamics [1], [3], [4]. In recent years, there has been an increasing interest in applying techniques from the domains of nonlinear analysis and chaos theory in studying the behavior of a dynamical system from an experimental time series such as EEG signals [5], [6]. The purpose of these studies is to determine whether dynamical measures especially Lyapunov exponents can serve as clinically useful parameters. Estimation of the Lyapunov exponents is computationally more demanding, but estimates of these parameters are more readily interpreted with respect to the presence of chaos, as positive Lyapunov exponents are the hallmark of chaos [7].

Medical diagnostic decision support systems have become an established component of medical technology. The main concept of the medical technology is an inductive engine that learns the decision characteristics of the diseases and can then be used to diagnose future patients with uncertain disease states. Neural networks have been used in a great number of medical diagnostic decision support system applications because of the belief that they have greater predictive power [8], [9]. Various methodologies of automated diagnosis have been adopted, however the entire process can generally be subdivided into a number of disjoint processing modules: preprocessing, feature extraction/selection, and classification (Fig. 1). Signal/image acquisition, artefact removing, averaging, thresholding, signal/image enhancement and edge detection are the main operations in the course of preprocessing. The accuracy of signal/image acquisition is of great importance since it contributes significantly to the overall classification result. The markers are subsequently processed by the feature extraction module. Feature extraction methods are subdivided into: 1) statistical characteristics and 2) syntactic descriptions. The module of feature selection is an optional stage, whereby the feature vector is reduced in size including only, from the classification viewpoint, what may be considered as the most relevant features required for discrimination. The classification module is the final stage in automated diagnosis. It examines the input feature vector and based on its algorithmic nature, produces a suggestive hypothesis [8].

In the present study, the computation of Lyapunov exponents was the basis for feature extraction from the EEG signals. More specifically, the EEG signals [10] were modelled using multilayer perceptron neural network (MLPNN). In order to reduce the dimensionality of the extracted feature vectors, statistics over the set of the Lyapunov exponents were used. The selected Lyapunov exponents defining the behavior of the EEG signals were used as inputs of the MLPNN. The MLPNN presented in this study was trained, cross validated and tested with the selected

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). In order to improve convergence rate, the presented MLPNN trained with the Levenberg-Marquardt algorithm.

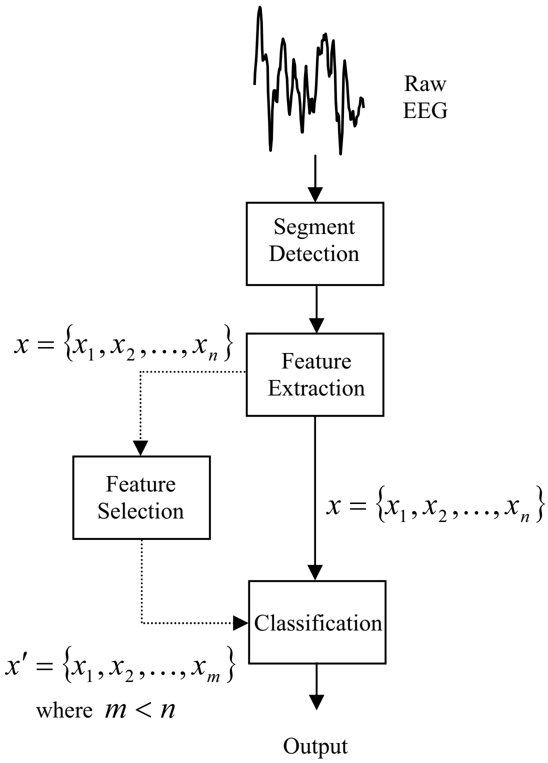


Fig. 1. Functional modules in a typical computerized electroencephalographic system

II. LYAPUNOV EXPONENTS

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 [11], [12]. 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,

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

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

The existence of a positive Lyapunov exponent indicates chaos. 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. Numerous methods for calculating the Lyapunov exponents have been developed during the past decade. Generally, the Lyapunov exponents can be estimated either from the equations of motion of the dynamic system (if it is known), or from the observed time series. The latter is what is of interest due to its direct relation to the work in this paper. The idea is based on the well-known technique of state space reconstruction with delay coordinates to build a system with Lyapunov exponents identical to that of the original system from which our measurements have been observed. Generally, Lyapunov exponents can be extracted from observed signals in two different ways. The first is based on the idea of following the time-evolution of nearby points in the state space. This method provides an estimation of the largest Lyapunov exponent only. The second method is based on the estimation of local Jacobi matrices and is capable of estimating all the Lyapunov exponents. Vectors of all the Lyapunov exponents for particular systems are often called their Lyapunov spectra [11], [12].

III. EXPERIMENTAL RESULTS

A. Feature Extraction by Computing Lyapunov Exponents

Selection of the artificial neural network (ANN) inputs is the most important component of designing the neural network based on pattern classification since even the best classifier will perform poorly if the inputs are not selected well. Input selection has two meanings: 1) which components of a pattern, or 2) which set of inputs best represent a given pattern. A rectangular window, which was formed by 256 discrete data, was selected so that it contained a single EEG segment. For each EEG segment, 128 Lyapunov exponents were computed. The following statistical features were used to reduce the dimensionality of the Lyapunov exponents:

1. Mean of the absolute values of the Lyapunov exponents in each segment.
2. Maximum of the absolute values of the Lyapunov exponents in each segment.
3. Average power of the Lyapunov exponents in each segment.
4. Standard deviation of the Lyapunov exponents in each segment.
5. Distribution distortion of the Lyapunov exponents in each segment.

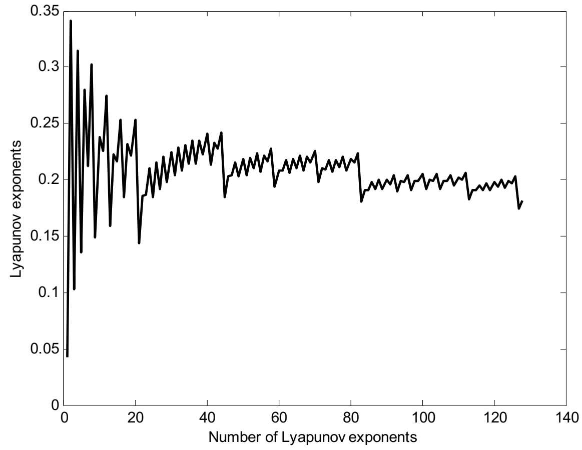
Features 1-5 represent the Lyapunov exponents distribution of the EEG signals. These feature vectors calculated for each segment were used for classification of the EEG signals.

B. Application of MLPNN to EEG Signals

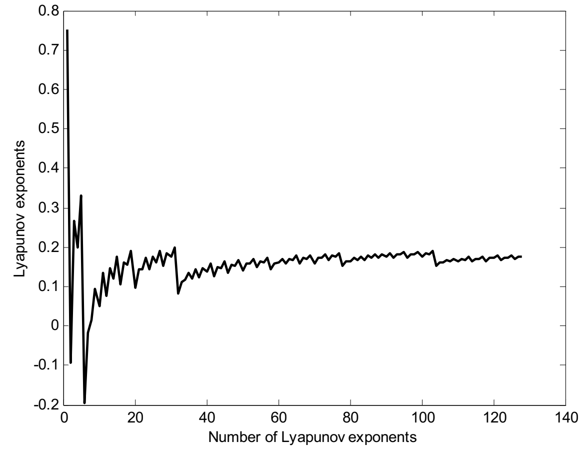
ANN architectures are derived by trial and error and the complexity of the neural network is characterized by the number of hidden layers. There is no general rule for selection of appropriate number of hidden layers. A neural network with a small number of neurons may not be sufficiently powerful to model a complex function. On the other hand, a neural network with too many neurons may lead to overfitting the training sets and lose its ability to generalize which is the main desired characteristic of a neural network. The most popular approach to finding the optimal number of hidden layers is by trial and error. 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 MLPNN was trained by using the Levenberg-Marquardt algorithm. For the Levenberg-Marquardt algorithm, the Marquardt parameter (γ) was set to 0.01. The MLPNN was implemented by using the MATLAB software package (MATLAB version 6.5 with neural networks toolbox).

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 Fig. 2(a)-(c), respectively. It can be noted that the Lyapunov exponents of the three types of EEG signals are different from each other. From Fig. 2(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 Fig. 2(b) and 2(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. There is a significant increase in the largest Lyapunov exponent values of the EEG signals recorded from epilepsy patients in the epileptogenic zone during a seizure-free interval comparing with the largest Lyapunov exponent values of the EEG signals recorded from healthy volunteers with eyes open and epilepsy patients during epileptic seizures. The Lyapunov exponents were computed using the MATLAB software package.

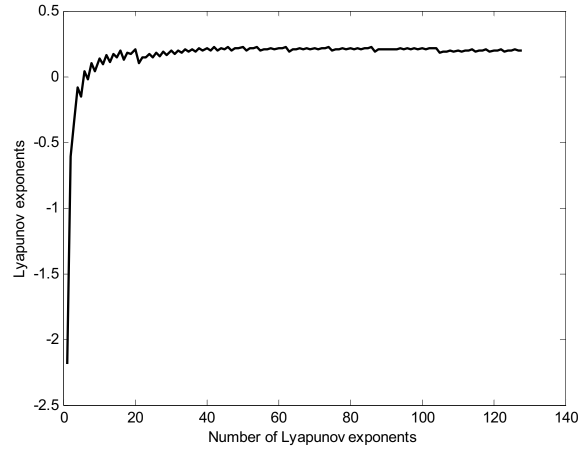
The feature vectors were calculated as explained in section 3.1. For the three diagnostic classes (set A - EEG signals recorded from healthy volunteers with eyes open, set D - EEG signals recorded from epilepsy patients in the epileptogenic zone during a seizure-free interval, and set E - EEG signals recorded from epilepsy patients during epileptic seizures) training and test sets were formed by 1200 vectors (400 vectors from each class) of 5 dimensions (selected Lyapunov exponents).



(a)



(b)



(c)

Fig. 2. 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)

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. Beside this, in order to enhance the generalization capability of the MLPNN, the training and the test sets were formed by data obtained from different subjects. For all of the segments, waveform variations were observed among the vectors belonging to the same class. When the error in the cross validation increased, the training was stopped because the point of best generalization had been reached. The MLPNN was trained in 700 epochs.

The outputs of the MLPNN were represented by unit basis vectors:
[0 0 1] = healthy segments
[0 1 0] = seizure free epileptogenic zone segments
[1 0 0] = epileptic seizure segments

The test performance of the MLPNN was determined by the computation of the following statistical parameters:
Specificity: number of correct classified healthy segments / number of total healthy segments
Sensitivity (seizure free epileptogenic zone segments): number of correct classified seizure free epileptogenic zone segments / number of total seizure free epileptogenic zone segments
Sensitivity (epileptic seizure segments): number of correct classified epileptic seizure segments / number of total epileptic seizure segments
Total classification accuracy: number of correct classified segments / number of total segments

The values of these statistical parameters are given in Table I. As it is seen from Table I, the MLPNN classified healthy segments, seizure free epileptogenic zone segments and epileptic seizure segments with the accuracy of 96.50%, 95.50% and 97.00%, respectively. The healthy segments, seizure free epileptogenic zone segments and epileptic seizure segments were classified with the accuracy of 96.33%.

TABLE I
THE VALUES OF STATISTICAL PARAMETERS

Statistical parameters	Values
Specificity	96.50%
Sensitivity (seizure free epileptogenic zone segments)	95.50%
Sensitivity (epileptic seizure segments)	97.00%
Total classification accuracy	96.33%

IV. CONCLUSION

For pattern processing problems to be tractable requires the conversion of patterns to features, which are condensed representations of patterns, ideally containing only salient information. Feature selection provides a means for choosing the features which are best for classification, based on various criteria. In the present study, feature extraction from the EEG signals was performed by the computation of Lyapunov exponents which determines the chaotic nature of the EEG signals. The dimensionality of the extracted feature vectors was reduced by the usage of statistics over the set of the Lyapunov exponents. The selected features were used as the inputs of the MLPNN trained with the Levenberg-Marquardt algorithm. The conclusions drawn in the applications demonstrated that the Lyapunov exponents are the features which are best representing the EEG signals and by the usage of the selected Lyapunov exponents best distinction between classes can be obtained.

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