COMBINED NEURAL NETWORK MODEL FOR DETECTION OF ELECTROCARDIOGRAPHIC CHANGES IN PARTIAL EPILEPTIC PATIENTS

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ABSTRACT
A combined neural network model based on the consideration that electrocardiogram (ECG) signals are chaotic signals was presented for detection of electrocardiographic changes in patients with partial epilepsy. This consideration was tested successfully using the nonlinear dynamics tools, like the computation of Lyapunov exponents. Two types of ECG beats (normal and partial epilepsy) were obtained from the MIT-BIH database. The computed Lyapunov exponents of the ECG signals were used as inputs of the combined neural network model and then performance of the proposed model was evaluated.

Key words: Combined neural network, Electrocardiographic changes, Partial epilepsy, Lyapunov exponents

I. INTRODUCTION
The electrocardiogram (ECG) signal is the recording of the bioelectrical and biomechanical activities of the cardiac system. It provides valuable information about the functional aspects of the heart and cardiovascular system. Epileptic seizures are associated with several changes in autonomic functions, which may lead to cardiovascular, respiratory, gastrointestinal, cutaneous, and urinary manifestations. Cardiovascular changes have received the most attention, because of their possible contribution to sudden unexplained death in epilepsy patients. The ECG should be reviewed for high risk cardiac abnormalities during epileptic seizures. A change in heart rate can be used as an extra clinical sign and can be very informative with respect to the first manifestation of the epileptic discharge [1, 2].

Many authors have shown that combining the predictions of several models often results in a prediction accuracy that is higher than that of the individual models [3-5]. The general framework for predicting using an ensemble of models consists of two levels and is often referred to as stacked generalization [6]. In the first level, various learning methods are used to learn different models from the original data set. The predictions of the models from the first level along with the corresponding target class of the original input data are then used as inputs to learn a second level model. As neural networks are among the most popular models for pattern classification, numerous studies that report on theoretical and experimental results on combining the neural network predictions can be found in the literature [3-5].

In this study, experimental results on combining neural network predictions for detection of electrocardiographic changes in partial epileptic patients were presented. The computation of Lyapunov exponents was the basis for feature extraction from the ECG signals. The ECG signals from the MIT-BIH database [7] were used to train and test the proposed model. A rectangular window, which was formed by 256 discrete data, was selected so that it contained a single ECG beat. In the development of combined neural network for the detection of electrocardiographic changes in partial epileptic patients, for the first level models we used two sets of neural networks because there were two possible outcomes of the detection of electrocardiographic changes (normal beat, partial epilepsy beat). In order to reduce the dimensionality of the extracted feature vectors, statistics were used over the set of the Lyapunov exponents. The selected Lyapunov exponents defining the chaotic behavior of the ECG signals were used as inputs of the first level neural network. Networks in each set were trained so that they are likely to be more accurate for one type of beat than the other beat. The predictions of the networks in the first level were combined by a second level neural network. We were able to achieve significant improvement in accuracy by applying neural networks as the second level model compared to the stand-alone neural network used in our previous study [2].

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 [2, 8]. 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,

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

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

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. 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 [2, 8].

III. COMBINED NEURAL NETWORK MODELS

Combined neural network models often result in a prediction accuracy that is higher than that of the individual models. This construction is based on a straightforward approach that has been termed stacked generalization. The stacked generalization concepts formalized by Wolpert [6] and refer to schemes for feeding information from one set of generalizers to another before forming the final predicted value (output). The unique contribution of stacked generalization is that the information fed into the net of generalizers comes from multiple partitionings of the original learning set. The stacked generalization scheme can be viewed as a more sophisticated version of cross validation and has been shown experimentally to effectively improve generalization ability of artificial neural network (ANN) models over using stand-alone neural networks [3-5].

The multilayer perceptron neural networks (MLPNNs) were used at the first level and second level for the implementation of the combined neural network proposed in this study. This configuration occured on the theory that MLPNN has features such as the ability to learn and generalize, smaller training set requirements, fast operation, ease of implementation. In both the first level and second level analysis, the Levenberg-Marquardt training algorithm was used.

IV. APPLICATION RESULTS

FEATURE EXTRACTION BY COMPUTING 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 ECG signals obtained from a normal subject and a subject with partial epilepsy are given in Figures 1 and 2, respectively. It can be noted that the Lyapunov exponents of the typical segment of ECG signals obtained from normal subject differ significantly from the Lyapunov exponents of the typical segment of ECG signals obtained from subject with partial epilepsy. As it is seen from Figures 1 and 2 there are positive Lyapunov exponents, which confirm the chaotic nature of the ECG signals obtained from normal subjects and subjects with partial epilepsy. The Lyapunov exponents were computed using the MATLAB software package.

For each ECG signal, 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 for each signal.
2. Maximum of the absolute values of the Lyapunov exponents for each signal.
3. Average power of the Lyapunov exponents for each signal.
4. Standard deviation of the Lyapunov exponents for each signal.
5. Distribution distortion of the Lyapunov exponents for each signal.

Features 1-5 represent the Lyapunov exponents distribution of the ECG signals. The feature vectors calculated for each signal were used for classification of the ECG beats.

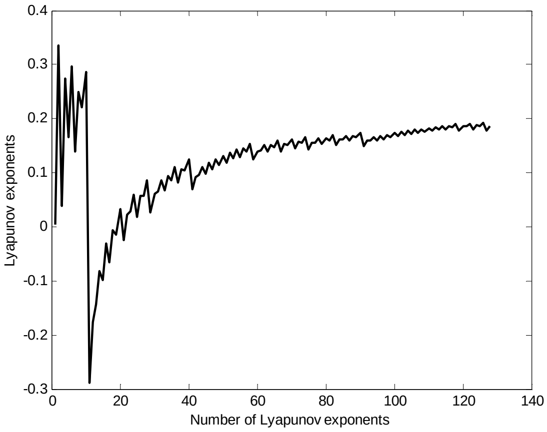

Figure 1. Lyapunov exponents of a typical normal ECG beat

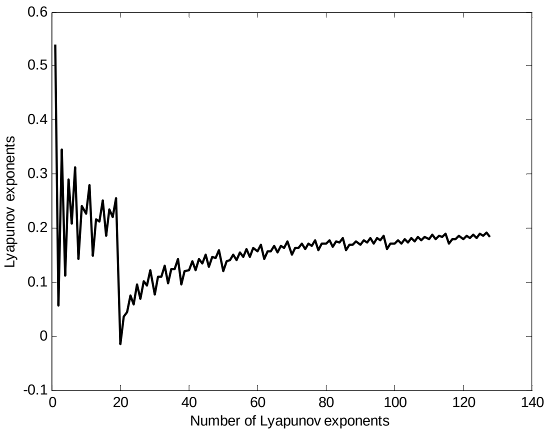

Figure 2. Lyapunov exponents of a typical partial epilepsy ECG beat

APPLICATION OF COMBINED NEURAL NETWORK MODEL TO ECG SIGNALS

The combined neural network topology used for the detection of electrocardiographic changes is shown in Figure 3. The network topology was the MLPNN with a single hidden layer. Each network had 5 input neurons, equal to the number of feature vectors (selected Lyapunov exponents). The feature vectors were calculated for each signal as explained in the section (feature extraction by computing Lyapunov exponents). Samples with target outputs normal beat and partial epilepsy beat were given the binary target values of (0,1), and (1,0), respectively. We trained second level neural network to combine the predictions of the first level networks. The second level network had 4 inputs which correspond to the outputs of the two groups of the first level networks. The targets for the second level network were the same as the targets of the original data.

In both the first level and second level, training of neural networks was done in 300 epochs since the cross validation errors began to rise at 300 epochs. Since the values of mean square errors (MSEs) converged to small constants approximately zero in 300 epochs, training of the neural networks with the Levenberg-Marquardt algorithm was determined to be successful. The adequate functioning of neural network depends on the sizes of the training set and test set. In this study, training and test sets were formed by 360 vectors (180 vectors from each class) of 5 dimensions (selected Lyapunov exponents). The 160 vectors (80 vectors from each class) of 5 dimensions were used for training and the 200 vectors (100 vectors from each class) of 5 dimensions 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 32 vectors (16 vectors from each class) of training set, which were selected randomly, were used as cross validation set.

The test performance of the combined neural network was determined by the computation of the following statistical parameters:
Specificity: number of correct classified normal beats / number of total normal beats
Sensitivity: number of correct classified partial epilepsy beats / number of total partial epilepsy beats
Total classification accuracy: number of correct classified beats / number of total beats

The values of these statistical parameters are given in Table 1. The normal beats and partial epilepsy beats were classified with the accuracy of 98.50%. The total classification accuracy of the stand-alone MLPNN presented in our previous study [2] (trained with the Levenberg-Marquardt algorithm, 128 Lyapunov exponents used as inputs) was 97.50%. Thus, the accuracy rates of the combined neural network model presented for this application were found to be higher than that of the stand-alone neural network model used in the previous study [2].

Table 1. The values of statistical parameters

Statistical parameters	Values
Specificity	99.00%
Sensitivity	98.00%
Total classification accuracy	98.50%

V. CONCLUSION

In order to classify the ECG beats, two sets of neural networks were trained. The learning targets were modified so that the trained networks would predict one particular beat with higher accuracy than the other type of beat. Improvement in accuracy was obtained by training new neural networks to combine the predictions of the original networks. The combined neural network used for the detection of electrocardiographic changes was trained, cross validated and tested with the computed Lyapunov exponents of the ECG signals obtained from normal subjects and subjects suffering from partial epilepsy. The dimensionality of the extracted feature vectors was reduced by the usage of statistics over the set of the Lyapunov exponents. The conclusions drawn in the applications demonstrated that the Lyapunov exponents are the features which are best representing the ECG signals and by the usage of the selected Lyapunov exponents in the combined neural network model best distinction between classes can be obtained.

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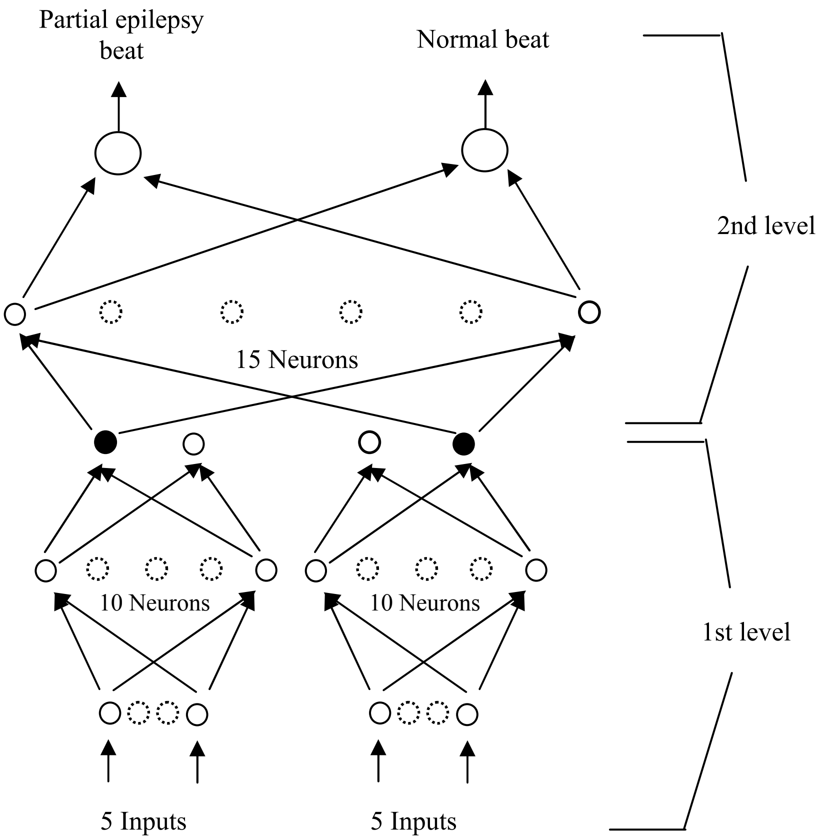

Figure 3. A combined neural network topology used for the detection of electrocardiographic changes