Delay Time-Based Epileptic EEG Detection Using Artificial Neural Network

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***Abstract*—The electroencephalogram (EEG) signal is very important for the diagnosis of epilepsy. The EEG recordings of the ambulatory recording systems generate very lengthy data and the detection of the epileptic activity requires a time-consuming analysis of the entire length of the EEG data by an expert. A neural-network-based automated epileptic EEG detection method is proposed in this paper, which uses delay time as the input feature of an artificial neural network. Mutual information method is applied in this paper for computing the delay time parameter of EEG signals. The results indicate that the delay time values of EEG signals during an epileptic seizure become larger than those of normal EEG signals obviously, and then this phenomenon is utilized for automated epileptic EEG detection combined with probabilistic neural networks (PNN). Delay time parameter is used as the input feature of the neural network for the first time for the detection of epilepsy. It is shown that the overall accuracy as high as 100% can be achieved by using the method proposed in this paper.**

Keywords-delay time; electroencephalogram (EEG); mutual information; artificial neural network (ANN); epilepsy; probabilistic neural network (PNN); seizure

I. INTRODUCTION

The electroencephalogram (EEG) is widely used to diagnose brain diseases in clinical applications, which is a recording of the electrical activity of the outer layer of the cerebral cortex [1], [2]. The recording of epileptic seizures is particularly helpful to doctors in the treatment of patients. Epilepsy is characterized by the occurrence of recurrent seizures in the EEG signal. In majority of the cases, the onset of the seizures cannot be predicted in a short period, a continuous recording of the EEG is required to detect epilepsy. A common form of recording used for this purpose is an ambulatory recording that contains EEG data for a very long duration of even up to one week [3]. It involves an expert's efforts in analyzing the entire length of the EEG recordings to detect traces of epilepsy. Because seizures, in general, occur frequently and unpredictably, automatic detection of seizures during long term EEG monitoring sessions is highly useful and needed. Over the past 20 years, numerous attempts to automate the detection of epileptiform activity have been made and comparatively good results have been obtained [3-7]. In this paper, we will propose another method for the automated detection of the epileptic seizure based on an artificial neural network, which utilize the difference of delay time between normal and epileptic EEG signals.

The brain can be considered as a nonlinear dynamic system, and the EEG signal is the set of continuous values varying as time of the nonlinear dynamic system, namely a time series. The basic method for the analysis of a time series is called phase space reconstruction, delay-coordinate embedding is adopted usually to reconstruct an equivalent phase space based on any component of the nonlinear dynamic system [8]. The choice of the delay time affects the results of the phase space reconstruction greatly, an appropriate delay time value can make the delay coordinate independent to the extreme extent, and the dynamic characteristic of the nonlinear dynamic system keep stable [9]. Actually, the delay time values can reflect the complexity of the EEG signal directly and the state of the function of the brain. In this paper, mutual information method is applied to compute the delay time of normal and epileptic EEG signals [10], and then the relationship between the delay time value and the epileptic seizure is analyze based on the results of delay time obtained by the mutual information method. Afterwards, the delay time is used as the input feature of the probabilistic neural network (PNN) for the automated detection of the epileptic seizure.

The paper is organized as follows: Section 2 describes the EEG data and the methods we used in this paper. Section 3 gives the simulations and the results of the detection. Section 4 concludes.

II. MATERIALS AND METHOD

A. Description of EEG time series

The signals used in this paper were obtained from a 16-channel EEG data acquisition card according to the international standard channel 10~20 system. Two groups of EEG signals were obtained, which were both from an epileptic, one group was collected when the patient was normal, and the other group was collected during an induced epileptic seizure. The sampling rate was 200Hz with the sampling time length of 80 seconds. Some of the EEG signals used in this paper are shown in Fig. 1 with the scalp electrode indices F3, C3, P3 and O1.

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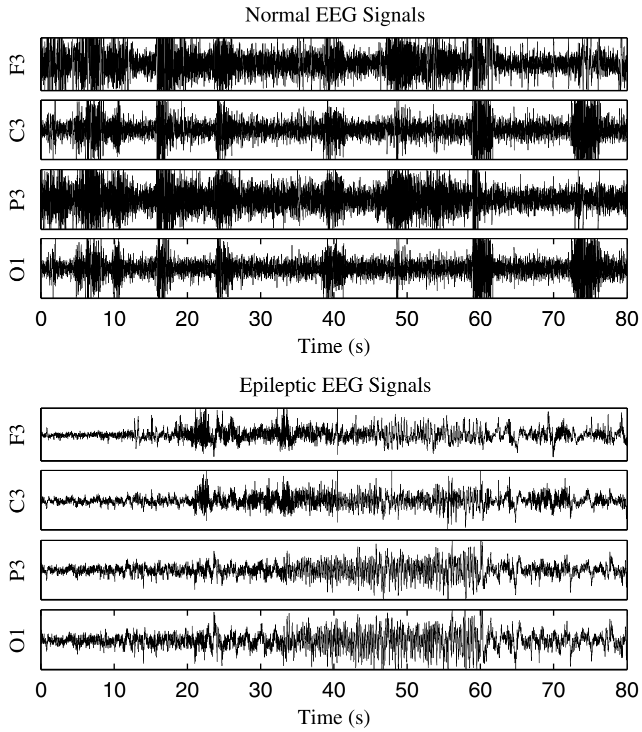

Fig.1 Normal and epileptic EEG signals

B. *Mutual information*

The method of mutual information is applied in this paper to compute the delay time parameter of EEG signals, which chooses the time corresponding to the first local minimum point of the mutual information function as the optical delay time [10]. Suppose there are two systems Q and S , based on the theory of information, the mutual information between Q and S can be defined as:

$$I(Q,S) = H(Q) + H(S) - H(Q,S) \quad (1)$$

where $H(Q)$ and $H(S)$ are the entropies of the systems Q and S; $H(Q,S)$ is the joint entropy function.

Consider S as the original data series $\{x(t)\}$ $(t = 1,2,\cdots,n)$, and Q as the T time delayed data series $\{x(t+T)\}$ of S, then the formula for calculating the mutual information can be written as:

$$I(Q,S) = \sum_i \sum_j P_{sq}(s_i, q_j) \log_2 \left[\frac{P_{sq}(s_i, q_j)}{P_s(s_i) P_q(q_j)} \right] \quad (2)$$

where $P_{sq}(s_i, q_j)$ is the joint distribution probability when $S = s_i$, $Q = q_j$, $P_s(s_i)$ and $P_q(q_j)$ are the marginal distribution probability.

Fig. 2 is an example for explaining how to determining the delay time of an EEG data segment in this paper. As the first minimum value point of the mutual information curve appears at (3,0.178) (see in Fig. 2, marked by an open circle), then the delay time parameter of this EEG data segment can be determined as 3.

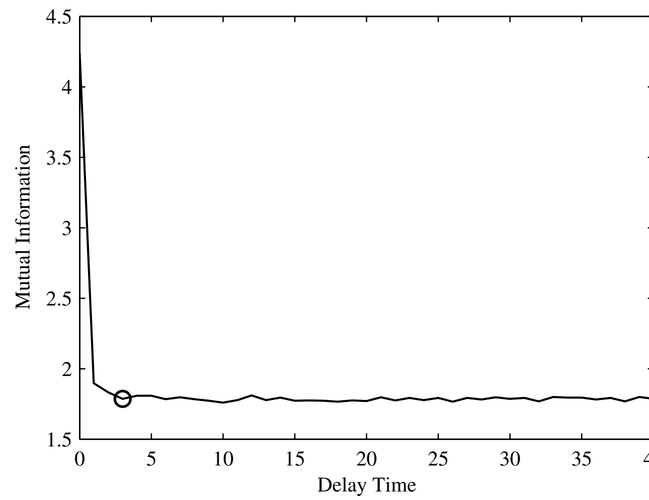

Fig. 2 Example for determining the delay time of an EEG segment

C. *Probabilistic neural network*

PNN is a type of radial basis network. It is a feedforward neural network with two middle layers called radial basis and competitive layers [11], [12]. The two layers employ radial basis and compete activation functions, respectively. Fig. 3 shows the architecture of a PNN. The delay time values corresponding to the normal and epileptic EEG signals are used as the input feature of the neural network. The network's target values correspond to a value of 1 for normal EEG and 2 for epileptic EEG.

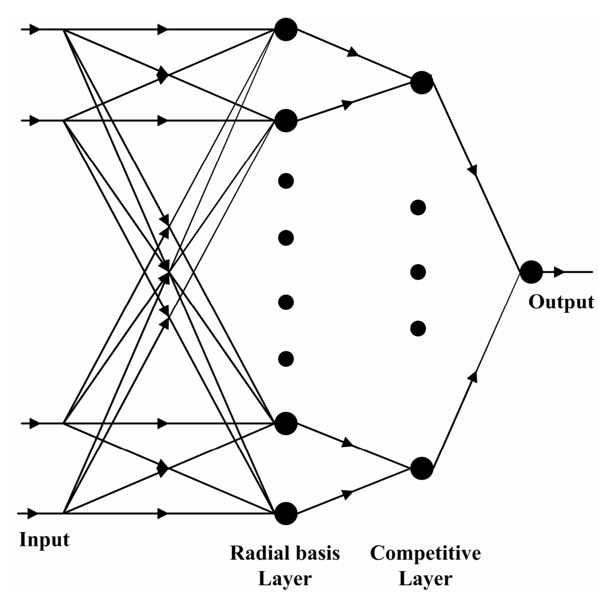

Fig. 3 Architecture of PNN

The performance of the PNN is evaluated by overall accuracy (OA), which are defined in (3) [1]:

$$OA(\%) = \frac{N_{CDP}}{N_{APP}} \times 100 \qquad (3)$$

where N_{CDP} represents the total number of correctly detected patterns and N_{APP} represents the total number of applied patterns. A pattern indicates both seizure and nonseizure.

III. SIMULATIONS

A. How the simulations are organized

If the dynamic system is invariant, then the determination of delay time can be made on any segment of the measured signal. This is not true in a time-varying environment. As the EEG signal is time-varying, dynamical measures should be computed within certain time scale, for which the local stationarity assumption is valid. If too long statistics to quantify the EEG are used, then the local information will be washed away, and most of the temporal characteristics will be deprived from their diagnostic values. Therefore, the EEG time series have to be divided into several small segments for computing delay time. The data we used here are 16-channel normal and epileptic EEG signals, the length of the signal is 80s for each channel, the sampling frequency is 200Hz, and therefore there are 16000 points for each channel signal. Each channel signal is divided into 16 segments, namely $S_1, S_2, \ldots, S_{16}$, each segment $S_i (i = 1,2,\ldots,16)$ is of 1000 points. Thus we can obtain 16 delay time values for each channel signal. As for the 16 channels of normal or epileptic EEG time series, we can get a 16*16 matrix built by the delay time values respectively.

PNN is used to discriminate normal and epileptic EEG signals after the seizure feature is extracted, which refers to the delay time parameters of the EEG signals in this paper. As the amount of the EEG data is limited, the data have to be divided into two groups, one group for training the artificial neural network, the other group for testing the performance of the neural network.

B. Feature extraction

Mutual information method is applied to compute the delay time of $S_i (i = 1,2,\ldots,16)$, parts of the results of delay time obtained by mutual information method corresponding to the former 8 channels of normal and epileptic EEG signals are shown in Table 1, in which for each cell the upper number corresponds to the delay time value of the epileptic EEG data segment and the lower number corresponds to the delay time value of the normal EEG data segment. The average values of delay time of the normal and epileptic EEG signals computed based on the delay time results of total EEG data segments are 3 for normal EEG signals and 7 for epileptic EEG signals, namely the average value of delay time of epileptic EEG signals is over 2 times larger than that of normal EEG signals. The standard deviation is computed based on the results of the delay times of normal and epileptic EEG signals, the results are 0.6143 for normal EEG signals and 1.2425 for epileptic EEG signals, which reflect that the delay time of epileptic EEG signals varies more intensely during seizure than that of normal EEG signals does. Fig. 3 is plotted based on the results of delay time, in which 16 pieces of dot curves stand for the delay time of the normal EEG signals and 16 pieces of dash curves for the delay time of epileptic EEG time series; it can be observed in Fig. 3 that the delay time of the normal or epileptic EEG signal does not keep constant all the time, the delay time curves corresponding to normal and epileptic EEG signals both vary in a belt, and the width of the variation belt constructed by the delay time curves corresponding to epileptic EEG signals is larger than that corresponding to normal EEG signals, which means that the delay time of epileptic EEG signals has a bigger variation interval than that of normal EEG signals.

As there is obvious difference between the delay time parameters of normal and epileptic EEG signals, it is considered to use this feature as the input of a PNN to detect epileptic seizure automatically.

TABLE I. RESULTS OF THE DELAY TIME OF NORMAL AND EPILEPTIC EEG SIGNALS

SE	Delay Time															
	S_1	S_2	S_3	S_4	S_5	S_6	S_7	S_8	S_9	S_{10}	S_{11}	S_{12}	S_{13}	S_{14}	S_{15}	S_{16}
Fp1	5 10	5 8	16 2	7 4	9 2	6 3	6 3	8 3	9 3	10 3	10 4	10 4	10 3	22 4	10 4	7 8
F3	6 3	6 3	6 2	6 3	2 4	4 4	5 3	5 2	9 3	10 4	12 3	6 2	10 12	14 2	5 8	12 4
C3	8 7	5 3	12 4	6 6	3 5	4 2	5 2	3 4	7 2	12 3	4 4	10 5	5 4	3 5	8 4	12 4
P3	9 2	7 2	7 2	5 2	7 2	9 4	5 3	7 4	10 2	11 3	7 2	7 2	8 3	5 4	12 3	10 3
O1	6 6	6 2	5 2	6 6	4 2	5 4	9 4	5 2	6 2	5 6	5 3	5 5	6 4	5 2	7 3	8 2
F7	6 2	6 2	5 4	6 4	3 4	3 2	6 3	4 3	6 3	8 2	5 1	4 3	4 3	2 5	3 3	11 1
T3	4 4	4 3	6 2	6 3	2 2	6 3	5 5	4 5	5 2	3 3	5 2	6 3	4 4	4 2	5 3	3 5
T5	4 5	3 3	4 2	8 3	3 2	7 10	6 3	7 3	8 2	6 2	6 2	9 3	13 6	3 6	8 3	11 6

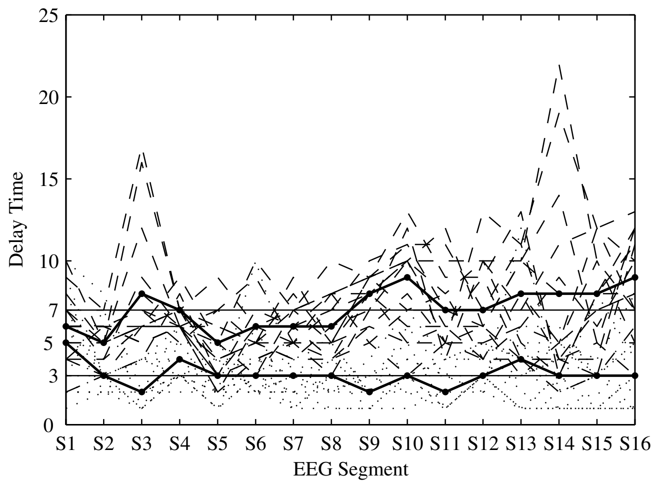

Fig. 4 Delay time values of normal and epileptic EEG signals obtained by the method of mutual information. (Note: The 16 dot curves correspond to the delay time values of 16-channel normal EEG signals and the 16 dash curves correspond to the delay time values of 16-channel epileptic EEG signals. The upper curve marked by black point is constructed by the average delay time values of epileptic EEG signals for the segment $S_i (i = 1,2,\cdots,16)$, the lower curve marked by black point is constructed by the average delay time values of normal EEG signals for the segment $S_i (i = 1,2,\cdots,16)$. The upper straight line corresponds to the average delay time value of epileptic EEG signals, and the lower straight line corresponds to the average delay time value of normal EEG signals.)

C. *Epileptic seizure detection*

Delay time values are computed for both normal and epileptic EEG signals, and are fed as input feature to the PNN. Among the available 16 pairs of normal and epileptic EEG data sets, 10 pairs are used for training and the remaining are used for testing the performance of the neural networks. Each channel of EEG signal, which has 16000 points totally, is divided into 16 frames, each frame has 1000 points, and the delay time values are computed for each data frame. 8-16 data frames of each channel are taken respectively as the input of the PNN to show the influence of the number of data points on the performance of PNN. The results of the performance test on 6 pairs of normal and epileptic EEG signals are shown in Table 2.

TABLE II. RESULTS OF THE DETECTION OF SEIZURE USING PNN

Number of Points	Number of Correct Detection		Overall Accuracy (%)
	Normal EEG	*Epileptic EEG*	
8	6	5	91.7
9	6	5	91.7
10	6	6	100
11	6	6	100
12	6	6	100
13	6	6	100
14	6	6	100
15	6	6	100
16	6	6	100

The results shown in Table 2 indicate that the overall accuracy of the discrimination between normal and epileptic EEG signals based on the PNN depends on the number of data frames of each channel of EEG signal, which is fed into PNN as input, the trend is that more data frames are taken, higher the overall detection accuracy is, when the number of data frames is over 9, the overall accuracy as high as 100% can be achieved.

IV. CONCLUSIONS

In this paper, the difference of delay time between normal and epileptic EEG signals are studied firstly, it is found that the delay time of normal and epileptic EEG signals both vary in a belt, and the delay time of EEG signals during seizure becomes larger than that of normal EEG signals; further the delay time is used as the input feature of an artificial neural network for the automated detection of epileptic seizure. PNN is employed for the automated detection of epileptic seizure. The results of simulations show that the overall accuracy of the detection as high as 100% can be achieved. As the proposed method is of low computation complexity and uses not too much EEG data, it is suitable for the real-world detection of epileptic seizure.

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