Detection of Epileptic Seizure Based on EEG Signals

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***Abstract*—In this paper, the support vector machines (SVMs) is adopted for distinguishing between normal and epileptic EEG time series. The embedding dimension of electroencephalogram (EEG) time series is used as the input feature for detecting epileptic seizure automatically. Cao's method is applied for computing the embedding dimension of normal and epileptic EEG time series. In the last work, probabilistic neural networks (PNN) was employed for detecting epileptic seizure automatically, therefore, the results obtained by SVMs are compared with those obtained by PNN in this paper. The results show that the overall accuracy as high as 100% can be achieved by both the methods; however, for the same accuracy, the experiment by SVM needs less input features than PNN.**

Keywords- Electroencephalogram (EEG); SVM; PNN; Seizure; Epilepsy

I. INTRODUCTION

Epilepsy, from which approximate 1% of the people in the world suffer, is a group of brain disorders characterized by the recurrent paroxysmal electrical discharges of the cerebral cortex, that result in irregular disturbances of the brain functions, which are associated with the significant changes of the EEG signal [1, 2]. Electroencephalograms (EEGs) are recordings of the electrical potentials produced by the brain. Analysis of EEG activity has been achieved principally in clinical settings to identify pathologies and epilepsies since Hans Berger's recording of rhythmic electrical activity from the human scalp. In the past, interpretation of the EEG was limited to visual inspection by a neurophysiologist, an individual trained to qualitatively make a distinction between normal EEG activity and abnormalities contained within EEG records [3]. It is known that biological neurons can be modeled by a set of nonlinear differential equations. The minimal embedding dimension gives the upper number of nonlinear dynamic system (NDS) freedom degrees and the minimal number of differential equations demanded for mathematical modeling of NDS [4]. Therefore, the change of the structure of brain NDS during seizure can be shown by the change of embedding dimension of EEG signals if the human brain is considered as a nonlinear dynamic system.

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 [5]. 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 epileptic form activity have been made and comparatively good results have been obtained [5-7]. 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 embedding dimension between normal and epileptic EEG signals.

II. MATERIALS

The EEG 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.

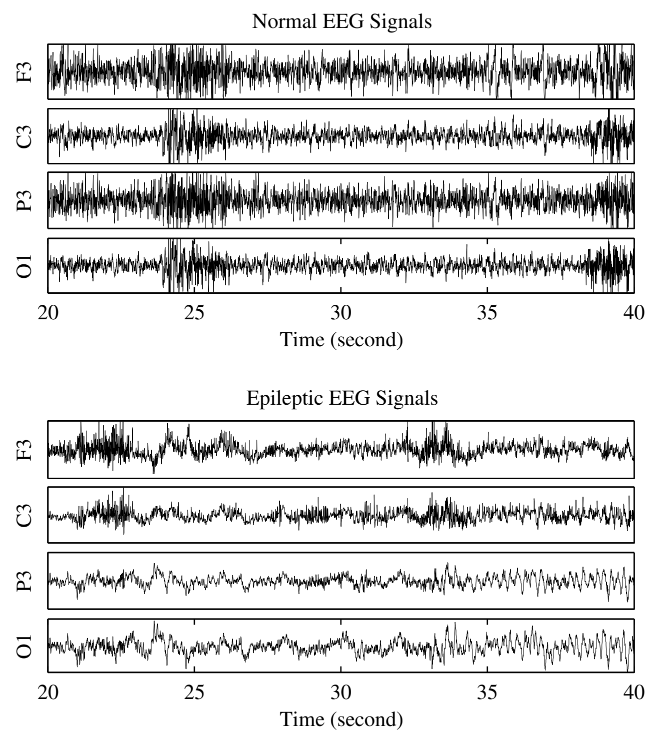

Fig.1 Normal and epileptic EEG signals

III. METHODS

A. Support Vector Machines

Support vector machines (SVMs) are build on developments in computational learning theory, and they are a set of related supervised learning methods used for classification and regression. In simple words, given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that predicts whether a new example falls into one category or the other. Intuitively, an SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. Because of their accuracy and ability to deal with a large number of predictors, they have more attention in biomedical applications. The majority of the previous classifiers separate classes using hyper planes that split the classes, using a flat plane, within the predictor space. SVMs broaden the concept of hyper plane separation to data that cannot be separated linearly, by mapping the predictors onto a new, higher-dimensional space in which they can be separated linearly.

The support vector classifier has many advantages. A unique global optimum for its parameters can be found using standard optimization software. Nonlinear boundaries can be used without much extra computational effort. Moreover, its performance is very competitive with other methods. A drawback is that the problem complexity is not of the order of the dimension of the samples, but of the order of the number of samples. For large sample sizes NS > 1000 general quadratic programming software will often fail and special-purpose optimizers using problem-specific speedups have to be used to solve the optimization.

B. Cao's Method

Cao's method [8] is applied in this paper to compute the embedding dimension of EEG time series. A brief introduction to Cao's method is given below:

Suppose that $x_1, x_2, \cdots, x_N$ is a time series, the embedding dimension can be determined by Cao's method as follows:

Reconstruct the time series like time delay vectors in phase space:

$$\begin{aligned} Y_i(d) &= [x(i), x(i+\tau), x(i+2\tau), \cdots, x(i+(d-1)\tau)], \\ &= 1,2,\cdots, N-(d-1)\tau \end{aligned} \tag{1}$$

where d is the embedding dimension and τ is the time delay. Note that $Y_i(d)$ means the *i*th reconstructed vector and

$Y_i^{NN}(d)$ as the nearest neighbor of $Y_i(d)$ in embedding dimension d as follows:

$$\begin{aligned} Y_i^{NN}(d) = [&x^{NN}(i), x^{NN}(i+\tau), x^{NN}(i+2\tau), \\ &\cdots, x^{NN}(i+(d-1)\tau)] \end{aligned} \tag{2}$$

Define

$$a_2(i,d) = \frac{\left\| Y_i(d+1) - Y_i^{NN}(d+1) \right\|}{\left\| Y_i(d) - Y_i^{NN}(d) \right\|} \tag{3}$$

here $\|\cdot\|$ is the Euclidian distance. $Y_i(d)$ is the *i*th reconstructed vector and $Y_i^{NN}(d+1)$ is its nearest neighbor in embedding dimension $d+1$. The mean value of all $a_2(i,d)$'s is defined as:

$$E(d) = \frac{1}{N-d\tau} \sum_{i=1}^{N-d\tau} a_2(i,d) \tag{4}$$

$E(d)$ is only dependent on the dimension d and lag τ. To investigate its variation from d to $d+1$, define

$$E_1(d) = E(d+1)/E(d) \tag{5}$$

$E_1(d)$ stops changing when d is greater than some value d_0, which is the minimum embedding dimension we look for.

Another quantity $E_2(d)$ which is useful to distinguish deterministic signals from stochastic signals is defined as follow:

$$E^*(d) = \frac{1}{N-d\tau} \sum_{i=1}^{N-d\tau} \left| x(i+d\tau) - x^{NN}(i+d\tau) \right| \tag{6}$$

$$E_2(d) = E^*(d+1)/E^*(d) \tag{7}$$

IV. EXPERIMENTS AND RESULTS

A. Feature Extraction

Cao's method is applied to compute the embedding dimension of $S_i (i = 1,2,\ldots,16)$, and the results are plotted in Fig. 4, 16 pieces of dot lines for normal EEG time series and 16 pieces of dash lines for epileptic EEG time series; it can be seen in Fig. 2 that the embedding dimension of normal or epileptic EEG time series is not a constant, they both fluctuate in a band, and the width of the fluctuation band constructed by the curves corresponding to epileptic EEG time series is much larger than that corresponding to normal EEG time series. The results obtained by Cao's method show that embedding dimension values can clearly discriminate between normal and epileptic EEG time series, thus the difference of embedding dimension between normal and epileptic EEG time series is utilized as the single input feature of the artificial neural network for the automated detection of epilepsy.

B. Epileptic Seizure Detection

As we did in the paper before, embedding dimension values are computed for normal and epileptic EEG signals, and are fed as input feature to the SVMs. Among the available 16 pairs of normal and epileptic EEG data sets, 8 pairs are used for training and the remaining are used for testing the performance.

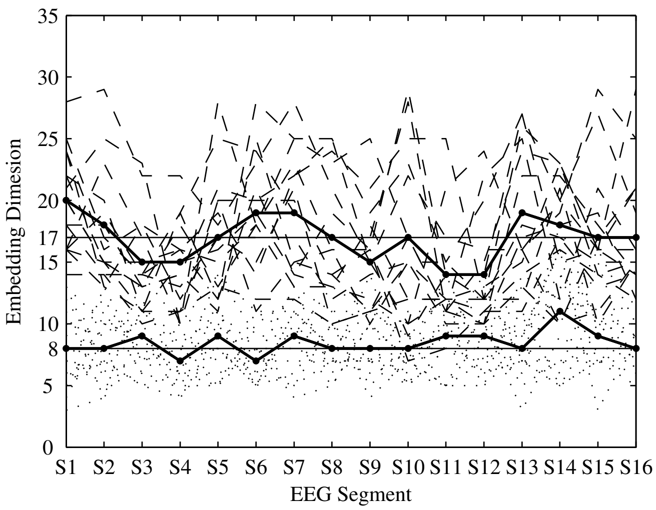

Fig. 2 Embedding dimensions of EEG signals obtained by Cao's method.

Each channel of EEG signal, which has 16000 points totally, is divided into 16 frames, each frame has 1000 points, and the embedding dimension is computed for each data frame. 8-16 data frames of each channel are taken respectively as the input of the SVMS to show the influence of the number of data points on the performance. The results of the performance test on 8 pairs of normal and epileptic EEG signals are shown in Table 1, in which the results of experiments by PNN are also listed for comparision.

The results shown in Table 1 indicate that the overall accuracy of the discrimination between normal and epileptic EEG signals based on the SVMS and PNN both depends on the number of data frames of each channel of EEG signal, the trend is that the more data frames are taken, the 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.

TABLE I. RESULTS OF EXPERIMENTS BY SVMS AND PNN

Numbers of Points	**Number of Correct Detection**		**Overall Accuracy (%)**	
	Normal EEG	***Epileptic EEG***	***SVMs***	***PNN***
8	8	7	95.1	93.7
9	8	7	96.3	93.7
10	8	8	100	100
11	8	8	100	100
12	8	8	100	100
13	8	8	100	100
14	8	8	100	100
15	8	8	100	100
16	8	8	100	100

Based on the results shown in Table 1, the performance of SVMS and PNN are close. The accuracy values for the detection of normal EEG time series are all equal to 100%, whereas the accuracy values for the detection of epileptic EEG time series is lower than 100% when the data points of each channel taken for inputting to the SVMs and PNN is less than 10. When the input feature vectors are less than 8, the accuracy of the experiments by SVMs is better than that by PNN; however, when the input feature vectors are larger than 9, the accuracy of experiments by SVMs and PNN are the same. So by comparison, it can be noticed that the performance of SVMs and PNN are close for distinguishing small amount of data, and at this time, the first factor that should be considered is the computation burden.

V. CONCLUSIONS

In the last work, PNN was used as a classifier for detecting epileptic seizure automatically. In this paper, another classifier-SVMs is adopted for distinguishing between normal and epileptic EEG time series, as we did before, the difference of embedding dimension between normal and epileptic EEG signals are calculated by Cao's method; further the embedding dimension is used as the input feature of SVMs for the automated detection of epileptic seizure. The results of experiments by SVMs and PNN were compared. The results of simulations show that the overall accuracy of the detection as high as 100% can be achieved for both the methods. As the proposed method is of low computation burden and uses not too much EEG data, it is suitable for the real-time detection of epileptic seizure.

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