Using Damping Time for Epileptic Seizures Detection in EEG

X. Li[1], X. Guan[2] and R. Du[1]

1. Dept. of Automation & Computer-Aided Eng., The Chinese University of Hong Kong, HK
2. Institute of Electrical Engineering, Yanshan University, Qinhuangdao 066004, P. R. China
Correspondent author's E-mail: xli_ysu@yahoo.com

Abstract: The dynamical characteristics of a complex system can be inferred from an observation of the system. In this paper, a calculation algorithm of the damping time of a signal from a complex system is presented by using information retrieve and autoregressive model. Two EEG recordings during tonic–clonic seizure are analyzed; the damping time of EEG calculated by means of the proposed algorithm can successfully identify the difference between the seizure and pre/post-seizure. In light of this we suggest that the concept of damping time of the EEG may find an application in the development of new detection method for epileptic seizures.

Keywords: Dynamic system; Embedding; Eigenmodes; EEG, Epileptic seizure.

1. INTRODUCTUION

It is known that the observation of a complex dynamic system can be considered as a projection from a lower dimension space to a higher dimension space, and hence, the states of the dynamic system may not be directly observable. This is true even if multiple simultaneous measurements are taken (Kantz and Schrieber, 1997). Nevertheless, the missing information can be recovered from time-delayed copies of the observation, if certain requirements are fulfilled (Abarbanel and *et al*., 1993). Referred to as the embedded theory, the basic idea for recovering the missing information is to use the correlation dimension to describe the dynamic characteristics of the system. This technique has been proved to be effective in a number of applications, such as EEG signal processing.

The long EEG recordings have been widely used to monitor epilepsy patients (Gotman, 1989). In this application, automatically detecting the epileptic seizures from the EEG recordings could be life–saving. In the past decade, various methods for identifying the epileptic seizures have been developed, such as the time-frequency analysis (Blance and *et al*., 1995), chaos method (Yaylali and *et al*., 1996), information theory (Kopitzki and *et al*., 1998), and the complex measure method (Bergey and *et al*. 2001).

This paper presents a new method, called the damping time method, for epileptic seizures detection. Intuitively, considering the human brain as a dynamic system, from an energy point of view, the damping time of an EEG signal is significant when the brain is normal. This is because the brain can exercise self-control. In contrast the damping time of the EEG signal will be small when the brain experiences an epilepsy seizure. The following of the paper is organized as follows. In Section 2, it shows that the damping time of a signal can be calculated using AR model. Section 3 presents two cases, in which the damping time of the EEG signals are used to detect the epileptic seizures. Finally, Section 4 contains the conclusions.

2. THE METHOD

2.1. Information retrieve

Let $\{\mathbf{x}(t)\}$, $\mathbf{x} \in \mathbb{R}^d$, be the states of a dynamic system. Then, the observation, also referred to as the signal, $s(t)$, $s \in \mathbb{R}$, can be considered as a projection, $s = f(\mathbf{x})$. In general, the observations, $\{s_n\} = \{f(\mathbf{x}_n)\}$ may not properly represent the (multidimensional) state responses of the dynamic system. Hence, a reconstruction is necessary. The most popular reconstruction technique is the method of delays. In this method, a new space, called the embedding space, are formed from the time-delay of the observations:

$$S_n = (s_{n-(m-1)t}, s_{n-(m-2)t}, \ldots, s_n) \quad (1)$$

where, m is the number of elements of the embedding dimension, t is the delay time or lag time. There are a number of methods for choosing the embedding parameters m and t . It turns out, however, that the optimal choice depends largely on the application.

There are a number of ways to find the embedding space. The autocorrelation function, mutual information, and visual inspection of the signal with various lags provide important information about the delay, while the false neighbor statistics gives guidance about the proper embedding dimension (Kantz and Schrieber, 1997). In this study, the mutual information is used to determine the delay. Mutual information takes into account nonlinear correlations. One has to compute

$$S = -\sum_{ij} p_{ij}(t) \ln \frac{p_{ij}(t)}{p_i p_j} \quad (2)$$

where for some partition on the real numbers p_i is the probability to find a time series value in the i-th interval, and $p_{ij}(t)$ is the joint probability that an observation falls into the i-th interval and the observation time t later falls into the j-th. In theory this expression has no systematic dependence on the size of the partition elements and can be quite easily computed. After the delay time is found, the optimal embedding dimension can be estimated accordingly. There are several methods for choosing the minimum embedding dimension, such as singular value decomposition, false neighbors, and etc. In this study, the method proposed by Cao (1997), which is similar to the false neighbor method, is used.

2.2. Estimation of damping time

For a m variable time series $\mathbf{x}_t \in \mathbb{R}^m$, a m variable AR(1) model is defined by

$$\mathbf{x}_t = \mathbf{m} + \mathbf{A}\mathbf{x}_{t-1} + \mathbf{e}_t, \ \mathbf{e}_t \sim N(\mathbf{0}, \mathbf{C}) \quad (3)$$

where, $\mathbf{m} \in \mathbb{R}^m$ is a vector of intercept for nonzero mean the time series; $\mathbf{A} \in \mathbb{R}^{m\times n}$ represents the coefficient of the AR model; and $\mathbf{e}_t$ is the uncorrelated random noise with mean zero, and $\mathbf{C} \in \mathbb{R}^{m\times n}$ covariance matrix.

Using the eigenvalue decomposition method (Neumaier and Schneider, 2001), it can be shown that:

$$\mathbf{A} = \mathbf{S}\mathbf{H}\mathbf{S}^{-1} \quad (4)$$

where, $\mathbf{S}$ is a nonsingular matrix and $\mathbf{H}$ = diag(l_k). Note that l_k, k = 1, 2, …, m, are the eigenvalues. With the eigenvalue decomposition, the state vector, $\mathbf{x}_t$, and the noise vectors, $\mathbf{e}_t$, can be represented as follows:

$$\mathbf{x}_t = \mathbf{S}\mathbf{x}'_t \quad \mathbf{e}_t = \mathbf{S}\mathbf{e}'_t \quad (5)$$

where,

$$\mathbf{x}'_t = (x_t^1, x_t^2, \cdots, x_t^m)^T$$
$$\mathbf{e}'_t = (e_t^1, e_t^2, \cdots, e_t^m)^T$$

Furthermore, the AR(1) model can be written as:

$$\mathbf{x}'_t = \mathbf{H}\mathbf{x}'_{t-1} + \mathbf{e}'_t \quad (6)$$

Since $\mathbf{H}$ is diagonal, the m variable AR(1) model can be simplified as m uni-variable models:

$$x_t^k = l_k x_{t-1}^k + e_t^k, \ k = 1, 2, \ldots, m \quad (7)$$

Hence, the expected values are:

$$x_t^k = l_k x_{t-1}^k, \ k = 1, 2, \ldots, m \quad (8)$$

In the complex plane, the expected values of the coefficients describe a spiral:

$$\left\langle x_{t+1}^k \right\rangle = l_k^l \left\langle x_t^k \right\rangle = (e^{-1/t_k} e^{(\arg l_k)i})^l \left\langle x_t^k \right\rangle \quad (9)$$

where, $t_k = -1/\log|l_k|$ is the damping time.

3. CASE STUDIES

Fig. 1 shows two EEG signals with tonic-clonic seizure that are preprocessed by a hybrid median filter (Wichman, *et al*., 1990). The data contains a total of 3 minutes with pre-seizure, the seizure and some post-seizure activities. The more details of the two data can be found in (Quian, *et al*., 1997).

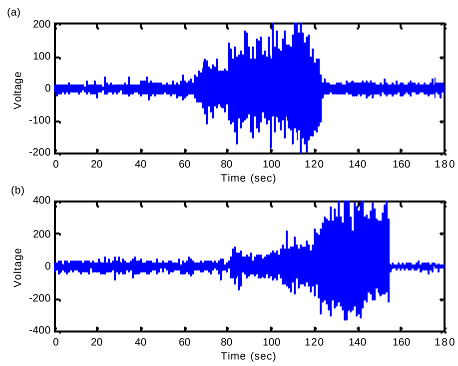

Fig. 1. EEG signals with tonic clonic seizure preprocessed.

First, the mutual information is used to determine the delay time. A segment of 60 second of the signal is extracted from the first signal, as shown in Fig. 2(a). To test the effect of the data length on the lag, the three different length: 2000 samples (A), 4000 samples (B) and 6000 samples (C) are selected, their auto mutual information are shown in Fig. 2(b). From Fig. 2(b), the first minimum of the auto mutual information can be found at six; Hence, the time delay is selected as six.

Next, Cao's method is employed to determine the minimal embedded dimension of the signal with the delay time of six. The results with three data sets of different length are shown in Fig. 3. From the figure it is seen that the embedding dimension is 10, since beyond which the performance does not improve much more.

Based on the time delay and the embedding dimension, a 10 dimensional time series is constructed. Accordingly, the 10-variable AR(1) model is formed and employed to calculate the damping time of the EEG from the each segments.

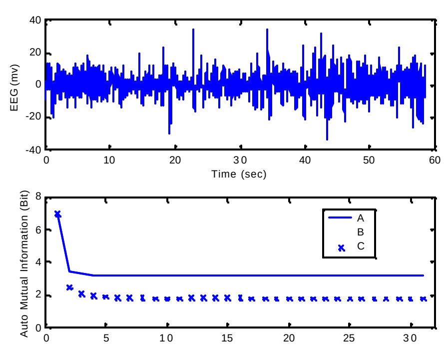

Fig. 2. (a) EEG signal during pre-seizure; (b) Auto mutual information with different data length.

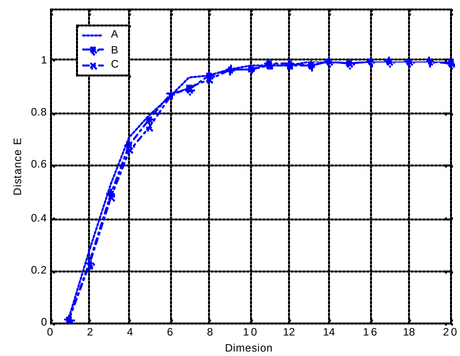

Fig. 3. The embedding dimensions with a delay time of 6, three nearest neighbors and 1000 reference points.

Fig. 1(a) shows a scalp EEG recording with tonic-clonic seizures. Seizures started at second 60 oral automatisms followed a few seconds later by a generalized tonic contraction. Fig. 4 shows the damping time of the EEG recording. This finding is that the damping time during the pre-seizure is longer than during the seizures. During the seizures the damping time is approximated to 0. After the end of seizure (second 120), the damping time is similar to during the pre-seizures.

Fig. 1 (b) shows another scalp EEG recording of a tonic-clonic seizure. Seizures started at second 80 oral automatisms followed 20 seconds later by a generalized tonic contraction. Fig. 5 shows the damping time of the EEG recording. The damping during the pre-seizure is longer than during the seizures. The same finding as the case 1 can be obtained also.

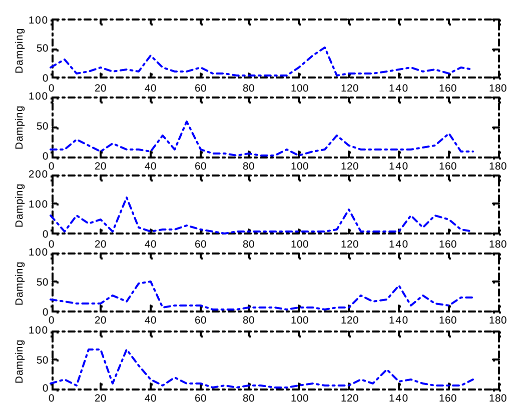

Fig. 4. The damping time of EEG recording of Fig. 1(a).

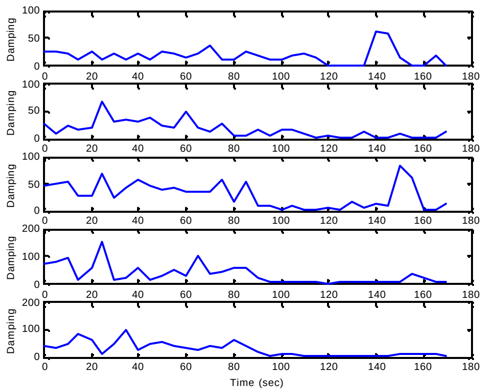

Fig. 5. The damping time of EEG recording of Fig. 1(b).

4. CONCLUSION

The aim of the paper is to address a novel approach with the information retrieve and the multivariate AR(1) model to calculate the damping time of a signal derived from a complex system. Application of the algorithm to the EEG signal with tonic-clonic seizures is performed. Based on the results, some conclusions can be made as follows:

(1) Mutual information and Cao's method can successfully determine the lag and minimum embedding dimension, which isn't influenced by the data length;

(2) The damping time of the EEG with tonic-clonic seizures can be calculated by the multivariate AR(1) model based on the high dimension time series constructed by embedded theorem. One finding is the damping time of EEG signal can identify the difference between the seizures and pre/post seizures. Perhaps, this dynamical characteristic, damping time, can be employed to detect the epileptic seizure in EEG.

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