SEIZURE PREDICTION BY NONLINEAR SMOOTHNESS ANALYSIS OF SCALP EEG RECORDING

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I. INTRODUCTION

Epilepsy is a neurological disorder which causes sudden bursts of synchronized brain activity named seizure. One of the most disabling aspects of the epilepsy is the unexpected instantaneous strike of epileptic seizures which can be a serious threat for the patient. Despite the apparent clinical unpredictability of the epileptic seizure, it has been shown that the transition from an interictal state to ictal state in epileptic brain may undergo a pre-ictal state in which the brain dynamics may have change. Nonlinear time series analysis of EEG signal is one of the powerful methods in detecting this preictal state and thus predicting an impending seizure [1]-[3].

There are major challenges, however, for application of these methods in complex and noisy EEG signals. Most of the applications of seizure prediction methods so far [1]-[3] have been concentrated on intracranial EEG (IEEG). IEEG is an expensive and invasive recording method which is usually performed only for pre-surgical evaluations. Surface scalp EEG, on the other hand can be recorded easily while it is much more susceptible to noise and artifact. Therefore, a reliable seizure prediction method based on scalp EEG recording with high robustness to noise is very demanding. In this paper, a univariate nonlinear measure has been proposed for seizure prediction using scalp EEG. The method is based on a modified robust measure of determinism using smoothness analysis [7][8][10] of the attractor in the phase-space. In this paper, it first shown that the proposed method is highly robust to added noise. The measure is also calculated here for EEG segments and its variation is studied before an epileptic seizure.

The rest of this paper is organized as follows. In sections II and III, the utilized method of determinism is first discussed and then tested on simulated time series. In section IV, results for healthy and epileptic EEG signals with one focal seizure are presented. Finally, in section V, the concluding remarks are discussed.

II. A METHOD FOR DETECTING DETERMINISM FOR SHORT TIME SERIES

In this paper, a method of determinism [8] for short time series based on surrogate data testing is implemented. The method calculates the smoothness of a trajectory in state space by measuring the irregularity of the successive tangent vectors along the trajectory. The entire trajectory of the system and hence a long time history of the signal is not needed. The method can be found in [8] and is briefly described as follows.

Suppose that a time series $x(n)$ is samples of the output of a differentiable deterministic dynamical system. The method of time delay embedding is first applied in order to reconstruct the state space trajectory in an *m*-dimensional embedding space [4]. The reconstructed trajectory consists of points defined by the following state vector

$$\vec{x}[n] = \left(x(n), x(n-T), \cdots, x(n-(m-1)T)\right)^{tr} \qquad (1)$$

where T is the time lag between selected samples of the time series, *m* is embedding dimension, and *tr* denotes transpose operation.

In the next step, the cosine function of the angles between successive tangent vectors $\vec{x}[n+2]-\vec{x}[n+1]$ and $\vec{x}[n+1]-\vec{x}[n]$ along the reconstructed trajectory is calculated and named as R_n. It has been shown [10] that the regularity of the angles may reflect smoothness of the trajectory while the smoothness is enough to imply determinism in the time series [7]. In order to measure the regularity of R_n, a second order difference plot (SODP) is defined [8] to plot ΔR_{n+1} versus ΔR_n where $\Delta R_n = R_{n+1} - R_n$.

Furthermore, the central tendency measure (CTM) is defined by the following formula to indicate a quantitative estimate of the variability in SODP and hence irregularity of the R_n values. Lower values of CTM correspond to higher regularity in R_n which represents determinism.

$$CTM = (M-2)^{-1} \sum_{n=1}^{M-2} \sqrt{\Delta R_{n+1}{}^2 + \Delta R_n{}^2} \qquad (2)$$

where M is total number of points.

In the last step, surrogate data testing is utilized to reject the null hypothesis that the time series represents linearly filtered random noise. Surrogate data are linear stochastic time series with the same linear and statistical parameters as the original time series. In this paper, amplitude adjusted Fourier transform method (AAFT) [9] is used which preserve both the power spectrum and the probability distribution of the original time series. A significance level (*p<0.01*) is selected and a statistical t-test is performed to reject the null hypothesis that CTM value of the time series and CTM values of its surrogates are not significantly different. Furthermore, the overall smoothness index (SI) is defined as the ratio of CTM of original time series CTM_o, to average CTM of its surrogates. Lower values of the SI indicate that the *CTM* for original time series and its surrogate are significantly highly different. It has been practically shown [8] that for stochastic time series SI is roughly greater than 0.7 and for deterministic time series SI is smaller than 0.3. The values of SI in between those levels can arise from a deterministic time series while further statistical tests are recommended for the method to be conclusive.

The above method is suitable for testing determinism of short time series. However, its main disadvantage is its poor robustness to additive noise. In the presence of noise, SI index increases up to the point when there is no significance difference between CTM of time series and its surrogates. Consequently, a signal corrupted by noise is falsely classified as stochastic and the real deterministic nature of the signal remains concealed under its noisy appearance. To overcome this problem, we propose an extension to the method [5], which is based on singular value decomposition (SVD) of the *trajectory matrix* of the time series. The trajectory matrix, *X* is defined as the matrix of all the state vectors placed in subsequent columns of a matrix. SVD can be written as $X = USV^{tr}$ where *S* is the diagonal matrix of singular values (σ) and *V* is the matrix of corresponding singular vectors. SVD provides a linear transformation (U^{tr}) that transforms the trajectory into a filtered delay embedding space. The transformed trajectory matrix, Y is then calculated as in equation 3 and represents a reconstructed attractor in the filtered delay coordinates corresponding with principal components.

$$\begin{aligned} Y &= U^{tr} X = [\vec{u}_1 \quad \vec{u}_2 \quad \cdots \quad \vec{u}_p]^{tr} X \\ &= SV^{tr} = [\sigma_1 \vec{v}_1 \quad \sigma_2 \vec{v}_2 \quad \cdots \quad \sigma_P \vec{v}_P]^{tr} \end{aligned} \qquad (3)$$

where *P* is total number of components.

Application of principal component analysis (PCA) as a filtered time delay embedding is well known [11][6]. It is usually expected that the directions in transformed embedding space with small corresponding singular values are mainly populated by noise. Therefore, PCA methods usually rely on truncating the singular spectrum based on the relative magnitude of singular values. In the present study, however, the approach is to keep all the components but analyze each component for underlying determinism. The proposed method is as follows. For each component *k,* the trajectory matrix constructed using only the *kth* singular value is determined by the following equation

$$X_k = \vec{u}_k \times \sigma_k \vec{v}_k^{tr} \qquad (4)$$

The smoothness index is then calculated for this trajectory and named as component smoothness index CSI_k. In order for the contribution of each singular value to be taken into account, an overall compensated component smoothness index (CCSI) is defined as the weighted average of all the component smoothness indexes as follows.

$$CCSI = \left(\sum_{k=1}^{P} \sigma_k^2 \times CSI_k \right) \Big/ \left(\sum_{k=1}^{P} \sigma_k^2 \right) \qquad (5)$$

where *P* is total number of components calculated in each embedding dimension. Furthermore the statistical significance level (the chance of the finding not to be true) for CCSI is named $\overline{p}$ and defined here as the same weighted average of significance levels *p* obtained by statistical t-test for any *CSI* to suppress the significance level of minor components while calculate the average significance.

III. SIMULATION RESULTS

The Lorenz time series was obtained by solving the following dynamical equations using a step size of 0.01.

$$\dot{x} = 10(y - x),\ \dot{y} = 28x - y - xz,\ \dot{z} = (-8/3)z + xy \qquad (6)$$

The method of time delay embedding is used here with a time lag T=1 and repeated using different embedding dimensions *m* up to 20. The SI calculated for 2000 samples of the Lorentz time series without any noise was always significantly smaller than 0.2 ($p<10^{-12}$). This clearly implies deterministic nature of the noiseless time series as expected. For the noisy time series, however, SI is not robust enough and increases even in the presence of small additive noise.

In order to study and compare the effect of noise on SI and the proposed CCSI, the above indexes are calculated for a Lorentz time series which are added with different levels of white noise. The noise level was defined as the ratio of the standard deviation of the noise to the main signal and the signal to noise ratio, SNR, is then expressed in dB unit. Figure 1 shows calculated SI and CCSI versus embedding dimension for a noisy time series when SNR=20 dB. SI is always near to 1 which does not imply determinism. However, CCSI can be significantly smaller than 0.3 (*p<0.01*) and detect the original determinism of the time series for embedding dimensions *m*>16. It implies that the effect of added noise on CCSI can be highly reduced when embedding dimension is increased. Figure 2 shows SI and CCSI calculated for different levels of noise and plotted versus SNR. Minimum tolerable SNR that keeps the index below the margin of 0.3 (and implies determinism) is about 46 dB for SI and 21 dB for CCSI. This increase in robustness is more significant at higher embedding dimensions.

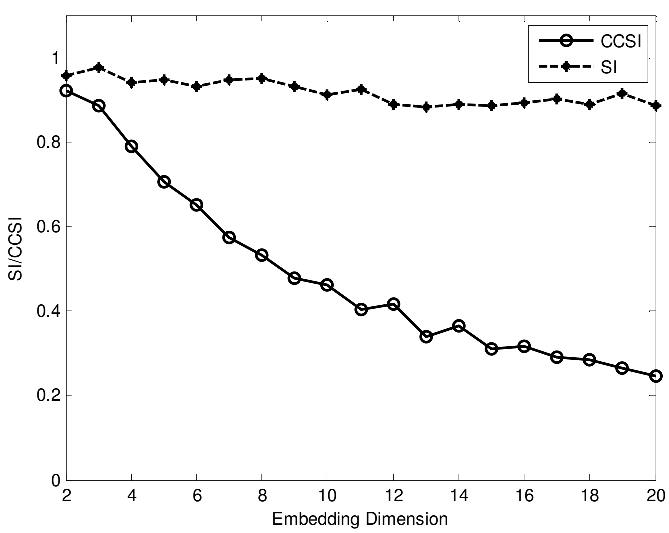

Figure 1: SI and CCSI at different embedding dimensions for noisy Lorenz time series SNR=20 dB

IV. DETERMINISM OF HEALTHY AND EPILEPTIC EEG SIGNALS

The above methods of detecting determinism were also applied to time series of digitally recorded scalp EEG signals. Signals were recorded for a healthy volunteer in relaxed state with a sampling rate of 200 Hz. A 10-20 standard monopolar recording montage with reference to average is used. Signals were band passed filtered between 1 and 70 Hz. 400 stationary segments of the signal (10 seconds each) in different channels were selected and tested for determinism. An embedding dimension *m* =11 and a time delay *T*=2 was used.

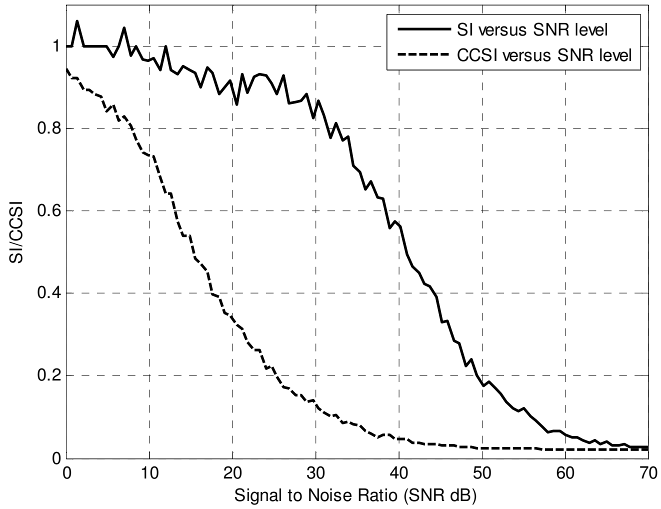

Figure 2: SI and CCSI versus noise level when normal white noise is added to Lorentz time series

As an example, SI and CCSI were calculated for one EEG segment recorded at channel P4 which mainly demonstrates normal alpha rhythm. Figure 3 shows calculated SI and CCSI plotted versus *m.* It is clear that smoothness index (SI) is always near 1 that concludes no determinism in this segment of EEG signal. CCSI however, drops to lower values of below 0.4 for large enough embedding dimensions (*m>10*). Significant level of all calculations is verified by surrogate data tests with *p<0.02.* Similar results were obtained for all the other selected segments.

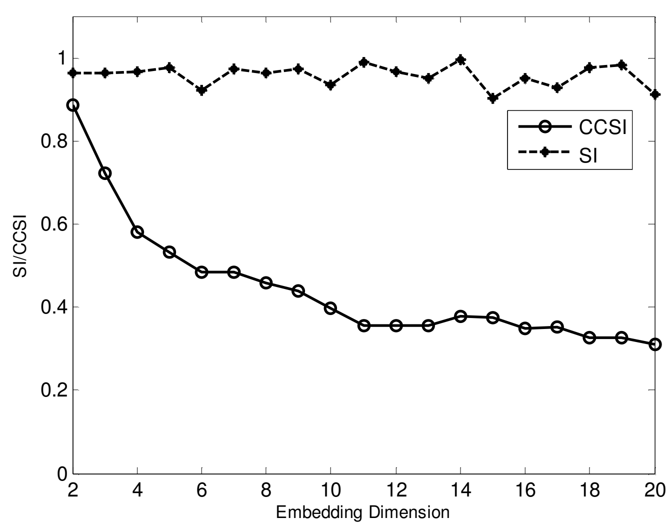

Figure 3: SI and CCSI versus *m* for one EEG segment

EEG signals are also recorded before a focal seizure occurs for an epileptic patient. The same method of recording described in the previous section was used. Signals were divided into subsequent segments of 10 seconds each and CCSI was calculated for each segment. An embedding dimension of m=11 and a time delay of T=2 was used. The time series of CCSI was then low pass filtered using a moving average filter with the frame size of 60 seconds. Variation of filtered CCSI for each channel is plotted versus time in Figure 4 for all channels. The time onset of the epileptic seizure is also marked on the figure. The only consistent and significant variation of CCSI which is observed prior to seizure is a shown to be a sharp increase and decrease in CCSI 8 and 4 minutes before the onset respectively. Variation of the CCSI after the seizure is not validated because of the large movement artifacts of the patient during the seizure activity. Although the significant variation of CCSI before the seizure can be associated to the impending seizure, more study is needed to verify the above results on different seizures and describe the reason behind these variations. Moreover, the sensitivity and false positive errors of any prediction should be investigated.

V. SUMMARY AND CONCLUSION

Prediction of epileptic seizures is very challenging for scalp EEG. The proposed method in this paper provides a robust method of testing determinism in time series using component analysis of the signal followed by analysis of smoothness. The method was used to detect changes in brain dynamics which may have useful information for seizure prediction. A significant change in determinism was detected on a seizure around 8 min in advance. The method should be tested on a large data set to validate the relation between seizure and observed changes.

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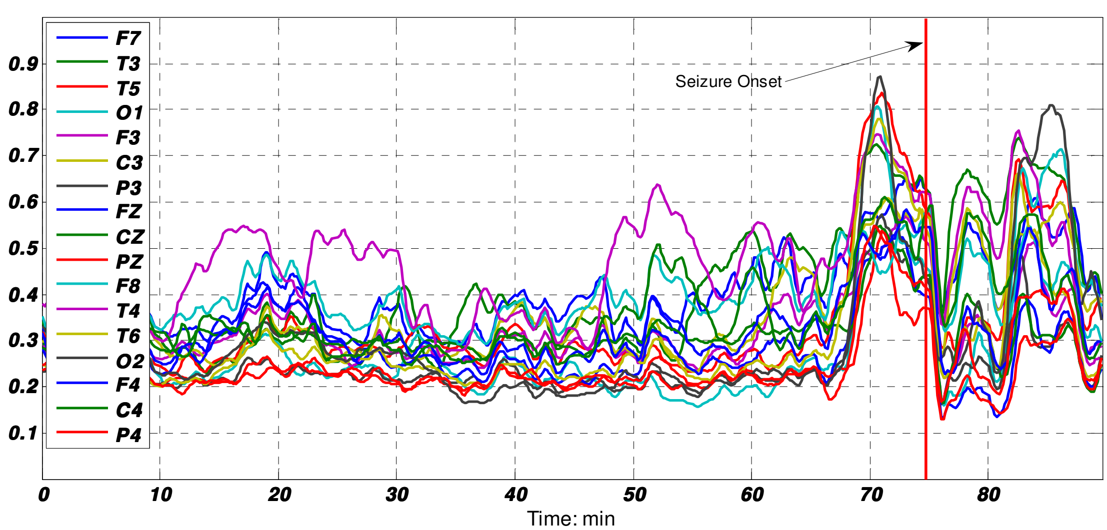

Figure 4: Filtered CCSI signal calculated for different channels and plotted versus time