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Ordinal pattern based similarity analysis for EEG recordings

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ABSTRACT

Objective: Ordinal patterns analysis such as permutation entropy of the EEG series has been found to usefully track brain dynamics and has been applied to detect changes in the dynamics of EEG data. In order to further investigate hidden nonlinear dynamical characteristics in EEG data for differentiating brain states, this paper proposes a novel dissimilarity measure based on the ordinal pattern distributions of EEG series.
Methods: Given a segment of EEG series, we first map this series into a phase space, then calculate the ordinal sequences and the distribution of these ordinal patterns. Finally, the dissimilarity between two EEG series can be qualified via a simple distance measure. A neural mass model was proposed to simulate EEG data and test the performance of the dissimilarity measure based on the ordinal patterns distribution. Furthermore, this measure was then applied to analyze EEG data from 24 Genetic Absence Epilepsy Rats from Strasbourg (GAERS), with the aim of distinguishing between interictal, preictal and ictal states.
Results: The dissimilarity measure of a pair of EEG signals within the same group and across different groups was calculated, respectively. As expected, the dissimilarity measures during different brain states were higher than internal dissimilarity measures. When applied to the preictal detection of absence seizures, the proposed dissimilarity measure successfully detected the preictal state prior to their onset in 109 out of 168 seizures (64.9%).
Conclusions: Our results showed that dissimilarity measures between EEG segments during the same brain state were significant smaller that those during different states. This suggested that the dissimilarity measure, based on the ordinal patterns in the time series, could be used to detect changes in the dynamics of EEG data. Moreover, our results suggested that ordinal patterns in the EEG might be a potential characteristic of brain dynamics.
Significance: This dissimilarity measure is a promising method to reveal dynamic changes in EEG, for example as occur in the transition of epileptic seizures. This method is simple and fast, so might be applied in designing an automated closed-loop seizure prevention system for absence epilepsy.

1. Introduction

The electroencephalogram (EEG) signal is a measure of the summed activity of approximately 1–100 million neurons lying in the vicinity of the recording electrode (Sleigh et al., 2004), and may provide insight into the functional structure and dynamics of the brain (Stam et al., 1999; Buzsaki, 2006). Therefore, the exploration of hidden dynamical structures within EEG signals is of both basic and clinical interests (Ouyang et al., 2008; Schad et al., 2008; Stacey and Litt, 2008). Recently, various methods have been used to analyze the temporal evolution of brain activity from EEG recordings (Stam, 2005; Mormann et al., 2007). They range from traditional linear methods, such as Fourier transforms and spectral analysis (Rogowski et al., 1981), to nonlinear methods derived from the theory of nonlinear dynamical systems (also called chaos theory), such as Lyapunov exponents (Wolf et al., 1985) and correlation dimension (Pritchard and Duke, 1995). To some extent, these chaos-based approaches are capable of extracting informative features from epilepsy EEG data (Iasemidis and Sackellares, 1996; Elger and Lehnertz, 1998; Lehnertz and Elger, 1998), sleep EEG data (Fell et al., 1993; Ferri et al., 2003) and anaesthesia EEG data (Watt and Hameroff, 1988; Widman et al., 2000), and moreover, these chaos-based approaches are more superior to the traditional linear methods (Rabinovich et al., 2006). However, chaos-based approaches assume that the signal is stationary and originates from a low dimensional nonlinear system. In reality, a real EEG is a non-stationary signal and stems from a highly nonlinear system (Gribkov and Gribkova, 2000). Therefore, chaos-based approaches must be used with care and caution in analyzing EEG data

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(Eckmann and Ruelle, 1992; Rapp, 1993). It is thus important to develop new methods to characterise EEG changes in different physiological and pathological states (Stam, 2005).

Recently, an ordinal time series analysis method was proposed by Bandt and Pompe (2002). This method measures the irregularity of non-stationary time series. The basic premise of this method is consideration of the order relations between the values of a time series and not the values themselves. The advantages of this method are its simplicity, robustness and low complexity in computation (Bandt and Pompe, 2002; Bandt et al., 2002) without further model assumptions. Also, the Bandt-Pompe method is robust in the presence of observational and dynamical noise (Bandt and Pompe, 2002; Rosso et al., 2007a). This method does show a fundamental distinction between deterministic chaos and noisy systems (Amigo and Kennel, 2007; Rosso et al., 2007b). These advantages facilitate the use of methods based on the Bandt-Pompe algorithm for investigating the intrinsic ordinal structures in complex time series from physical systems (Amigo et al., 2005, 2007; Amigo and Kennel, 2007, 2008; Bahraminasab et al., 2008; Bandt, 2005; Bandt and Shiha, 2007; Keller and Wittfeld, 2004; Keller and Sinn, 2005; Keller et al., 2007a; Rosso et al., 2007a,b; Zunino et al., 2008) and physiological systems (Bruzzo et al., 2008; Cao et al., 2004; Frank et al., 2006; Groth, 2005; Jordan et al., 2008; Keller et al., 2007b; Li et al., 2007a, 2008; Olofsen et al., 2008; Staniek and Lehnertz, 2007). In this paper, we have considered ordinal pattern distributions of EEG time series as a whole. We first counted the occurrences of each ordinal pattern and obtained the ordered rank–frequency distribution. Then, we quantified the "distance" between the rank–frequency distributions, called a dissimilarity measure. This dissimilarity measure was then used to investigate the dynamical characteristics of epileptic EEG data.

2. Methods

Given a time series, $x_1, x_2, \ldots, x_N$, an application of an embedding procedure was used to generate $N(m1)\tau$ vectors $X_1, X_2, \ldots, X_{N(m1)\tau}$ defined by: $X_t = [x_t, x_{t+\tau}, \ldots, x_{t+(m-1)\tau}]$ with the embedding dimension, m, and the lag, τ. This vector X_t can be rearranged in an increasing order as follows: $[x_{t+(j_1-1)\tau} \leqslant x_{t+(j_2-1)\tau} \ldots \leqslant x_{t+(j_m-1)\tau}]$. To obtain an unique result, we set $j_{r-1} < j_r$ in the case of $x_{t+(j_{r-1}-1)\tau} = x_{t+(j_r-1)\tau}$. For m different numbers, there will be $m! = 1 \times 2 \times \cdots \times m$ possible ordinal patterns π, which are also called permutations. As shown in Fig. 1(A), for $m = 3$, there are six possible ordinal patterns between x_t, $x_{t+\tau}$ and $x_{t+2\tau}$. Fig. 1(B) illustrates the definition of ordinal patterns for the sine function (left) and white noise time series (right), with $m = 3$ and $\tau = 1$. Based on these ordinal patterns, a new ordinal sequence π_i can be obtained. To further develop the statistical analysis of ordinal pattern distributions, we counted the occurrences of the ordinal patterns π, which was denoted as $C(\pi)$, then the relative frequency was calculated by $p(\pi) = C(\pi)/(N-(m-1)\tau)$, as is shown in Fig. 1(C). These were then re-sorted in order of descending frequency, to obtain a rank–frequency distribution $p(\pi_R)$, plotted in Fig. 1(D)), which represents the statistical hierarchy of ordinal sequences in the original time series. For example, the first rank pattern π corresponds to one type of ordinal pattern, which is the most frequent pattern in the time series. In contrast, the last rank pattern π indicates that this pattern is the weakest in the time series.

As shown in Fig. 1(D), the distributions of ordinal patterns of the sine function and white noise time series were quite different. With the white noise time series, with the characteristics of random processes, the probability distribution should be even since any ordinal pattern has the same probability of occurrence when the time series is long enough to exclude statistical fluctuations. However, when the series corresponds to a deterministic process, as in the example of the sine function, there are some patterns that will be encountered frequently in the time series due to the underlying deterministic structure. Therefore, we can quantify the "distance" between the rank–frequency distributions to measure dissimilarity between two time series, and this is given by

$$D_m(X,Y) = \sqrt{m!/m!-1}\sqrt{\sum_{i=1}^{m!}(p_X(\pi_{Ri}) - p_Y(\pi_{Ri}))^2} \quad (1)$$

where $p_X(\pi_{Ri})$ and $p_Y(\pi_{Ri})$ represent the rank frequencies of the time series X and Y, respectively. This measure ranges from 0 to 1 ($0 \leqslant D_m \leqslant 1$). When $D_m = 0$, it indicates that the rank–frequency ordinal patterns distribution in the two series is identical. In contrast, $D_m = 1$ indicates that one of the two series is totally different.

Therefore, a crucial parameter in this dissimilarity measure method is the choice of embedding dimension, m. When m is too small (less than 3) the scheme will not work well, since there are only very few distinct states for the time series. On the other hand, the length of the time series should be larger than $m!$ in order to achieve a proper differentiation between stochastic and deterministic dynamics (Staniek and Lehnertz, 2007). In order to allow every possible ordinal pattern of dimension m to occur in a time series of length N, the condition $m! \leqslant N-(m-1)\tau$ must hold and, moreover, $N >> m! + (m-1)\tau$, to avoid undersampling (Amigo et al., 2007). For this reason, given a dimension of length m, we need to choose $N \geqslant (m+1)!$. To satisfy this condition, we therefore chose only a low dimension m = 4 or m = 5 for the dissimilarity measure for this study.

3. Simulations

3.1. Neural mass model

A neural mass model, known as the nonlinear lumped-parameter cerebral cortex (LPCC) model (Lopes da Silva et al., 1974; Jansen and Rit, 1995; Wendling et al., 2000), was used to test the performance of this new method in this study. The following set of six differential equations governed the model:

$$\begin{cases} \dot{y}_0(t) = \dot{y}_3(t), \\ \dot{y}_3(t) = AaS(y_1 - y_2) - 2ay_3(t) - a^2y_0(t), \\ \dot{y}_1(t) = \dot{y}_4(t), \\ \dot{y}_4(t) = Aa\{p(t) + C_2S[C_1y_0(t)]\} - 2ay_4(t) - a^2y_1(t), \\ \dot{y}_2(t) = \dot{y}_5(t), \\ \dot{y}_5(t) = Bb\{C_4S[C_3y_0(t)]\} - 2by_5(t) - b^2y_2(t). \end{cases} \quad (2)$$

All the values of parameters in the model were set based on a physiological basis, the details of which can be found in Jansen and Rit (1995), Wendling et al. (2000)). In the model, the intra-population behavior is primarily influenced by the excitatory neuron parameter, A, and the inhibitory neuron parameter, B. The parameters A and B modulate the balance of excitation and inhibition ($h_e(t) = u(t)Aate^{-at}$ and $h_i(t) = u(t)Bbte^{-bt}$). By altering the excitatory and inhibitory parameters, the model can produce signals that strongly resemble intracranial EEG recordings (Wendling et al., 2000).

In this study, the extrinsic input $p(t)$ represents a Gaussian white noise with assigned mean value and variance (mean(p) = 75, std(p) = 25), which describes the overall density of action potentials coming from other regions. For each simulation described below, the differential equations were solved numerically using a fourth–fifth order Runge–Kutta algorithm. Initial conditions were set to zero in all simulations, and an integration step size of 5 ms was used. The first 1000 points of the simulated signals were discarded in order to avoid transient behavior.