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Using max entropy ratio of recurrence plot to measure electrocorticogram changes in epilepsy patients

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HIGHLIGHTS

- A maximum entropy ratio (MER) method is firstly adapted to investigate the ECoG data from epilepsy patients.
- The values of MER at the ictal state are significantly different with that at the interictal state.
- MER in the ECoG might be a potential characteristic of epileptic dynamics.

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ABSTRACT

A maximum entropy ratio (MER) method is firstly adapted to investigate the high-dimensional Electrocorticogram (ECoG) data from epilepsy patients. MER is a symbolic analysis approach for the detection of recurrence domains of complex dynamical systems from time series. Data were chosen from eight patients undergoing pre-surgical evaluation for drug-resistant temporal lobe epilepsy. MERs for interictal and ictal data were calculated and compared. A statistical test was performed to evaluate the ability of MER to separate the interictal state from the ictal state. MER showed significant changes from the interictal state into the ictal state, where MER was low at the ictal state and is significantly different with that at the interictal state. These suggest that MER is able to separate the ictal state from the interictal state based on ECoG data. It has the potential of detecting the transition between normal brain activity and the ictal state.

1. Introduction

Detection of dynamical changes in complex systems is one of the most important problems in physical, medical, engineering, and economic sciences [1]. Especially in medicine, accurate detection of transitions from a normal state to an abnormal state may improve diagnosis and treatment [2,3]. Recurrence plot, a two-dimensional graphical plot which shows the recurrences of states [4], is an important method for detecting dynamical changes [5]. It can uncover hidden periodicities in a signal in recurrence domain which are not easily noticeable [6]. The detection of recurrence domains has become increasingly important in recent years in the neurosciences [7,8]. Except for the recurrence plot, a number of interesting

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methods have been proposed to detect dynamical changes during the last two decades, including, recurrence quantification analysis [9,10], recurrence time statistics based approaches [11,12], space–time separation plots [13], recurrence plots of dynamical systems with nontrivial recurrences [14], recurrence plot statistics [15], base scale entropy [16], and nonlinear cross prediction analysis [17]. Most of these methods are based on quantifying certain aspects of the nearest neighbors in the phase space, and thus are computationally expensive.

Graben et al. proposed a novel algorithm for detecting recurrence domains from measured or simulated time series [18]. This symbolic analysis approach was successfully used for segmentation of event-related potentials into quasi-stationary states and providing an application to human language processing [19]. Its starting point is Eckmann et al.'s recurrence plot (RP) method for visualizing Poincare's recurrences [4]. Based on that, the authors proposed a maximum entropy ratio (MER) method, which is obtained by transforming the traditional recurrence plot to symbolic recurrence plot. The proposed method is numerically less time-consuming and advantageous especially for high-dimensional data since it simply exploits the recurrence structure of a system's dynamics. MER is a good estimator for a symbolically encoding for its adaptability, need of only a few parameters and wide application in various complex signals. Moreover, MER-based methods can provide quantified results and facilitate statistical analysis.

In this study, we applied the MER method on multi-dimensional Electrocorticogram (ECoG) data collected from epilepsy patients, to investigate whether MER could be used to detect epileptic seizures from ECoG data. The reminder of the paper is organized as follows. In Section 2, we explain the data acquisition and the computation process of MER. In Section 3, we present the MER results for both interictal and ictal states. The paper closes with a discussion on MER's potential usage in epilepsy studies.

2. Material and methods

2.1. ECoG data

In this study, ECoG data were retrospectively analyzed from the patients undergoing pre-surgical evaluation for drug-resistant temporal lobe epilepsy. Since the localization of the epileptic focus could not be accomplished by means of noninvasive EEG recordings, intracranial electrodes were chronically implanted for the purpose of identifying the focal seizure origin. Eight patients (age: 15–41, 4 male and 4 female) were chosen for dynamical analysis of their stored pre-surgical ECoG recordings (more than 20 h and include 18 seizures). These patients achieved complete seizure control after surgery so the epileptic focus can be assumed to be contained within the resected area. The patients had signed informed consent that their clinical data might be used and published for research purposes, and the study protocol had previously been approved by the ethics committee of Xuanwu Hospital, Capital Medical University. The ECoG data were acquired using a Neurofile NT digital video EEG system with 128 channels, and then sampled at 256 Hz by a 16-bit analog-to-digital converter, and filtered within a frequency band of 0.5–80 Hz.

2.2. The MER method

2.2.1. Symbolic recurrence plot

Let $x_i,\ i = 1, \ldots, N$ be the ith point on the orbit describing a dynamical system in a phase space and N be the number of points in the times series for analysis. To calculate MER, a recurrence plot (RP) visualizing the time dependent behavior of x_i is constructed. RP is a $N \times N$ matrix

$$R_{i,j} = \begin{cases} 1 : \left\|x_j - x_i\right\| \le \varepsilon \\ 0 : \text{Otherwise} \end{cases} \quad i, j = 1, \ldots, N \tag{1}$$

where $\|\cdot\|$ is the norm, ε is the cutoff distance defining an area centered at x_i. The optimal ε is determined by the maximal entropy algorithm described in Section 2.2.2. The L_∞-norm is selected, because it is computationally fast and allows to study some features in RPs analytically. RP can be represented as an $N \times N$ matrix of black and white tiles in time related space, where a black tile means recurrence has occurred (an example RP is shown in Fig. 1(a)).

Then, the RP is updated to form a symbolic RP, by a cluster comparison process. Fig. 2 shows the flowchart, while Fig. 1(b)–(d) gives examples of intermediate results (see Table 1). This process can be described by the following steps:

Step 1. Define a cluster list for the RP, in which each cluster contains the indices of black tiles of each row in the RP. For the 7 × 7 RP in Fig. 1, a cluster list of 7 clusters can be obtained.

Step 2. Test if the cluster list is empty. If yes, the calculation ends. Otherwise, create a new empty cluster.

Step 3. Choose one cluster from the cluster list which has not been compared with the new cluster. If the new cluster is empty, add its black tiles' indices to the new cluster, and remove it from the cluster list. For the current plot in Fig. 1(a), pick cluster 1 (row 1), put its index 1 and 4 into the new cluster, then remove it from the cluster list. Otherwise, compare it with the new cluster.

Step 4. If the chosen cluster has the same index as the new cluster, merge its indices into the new cluster and remove the cluster from the cluster list. For the example in Fig. 1(a), cluster 2 has the same index 4 with the new cluster, so its data 2, 4, 6, are merged into the new cluster, and cluster 2 is removed from the cluster list.