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Quantitative complexity analysis in multi-channel intracranial EEG recordings form epilepsy brains

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Abstract

Epilepsy is a brain disorder characterized clinically by temporary but recurrent disturbances of brain function that may or may not be associated with destruction or loss of consciousness and abnormal behavior. Human brain is composed of more than 10 to the power 10 neurons, each of which receives electrical impulses known as action potentials from others neurons via synapses and sends electrical impulses via a sing output line to a similar (the axon) number of neurons. When neuronal networks are active, they produced a change in voltage potential, which can be captured by an electroencephalogram (EEG). The EEG recordings represent the time series that match up to neurological activity as a function of time. By analyzing the EEG recordings, we sought to evaluate the degree of underlining dynamical complexity prior to progression of seizure onset. Through the utilization of the dynamical measurements, it is possible to classify the state of the brain according to the underlying dynamical properties of EEG recordings. The results from two patients with temporal lobe epilepsy (TLE), the degree of complexity start converging to lower value prior to the epileptic seizures was observed from epileptic regions as well as non-epileptic regions. The dynamical measurements appear to reflect the changes of EEG's dynamical structure. We suggest

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that the nonlinear dynamical analysis can provide a useful information for detecting relative changes in brain dynamics, which cannot be detected by conventional linear analysis.

Keywords

Dynamical system; Complexity analysis; Electroencephalogram (EEG); Minimum embedding dimension

1 Introduction

Epilepsy is a brain disorder characterized clinically by temporary but recurrent disturbances of brain function that may or may not be associated with destruction or loss of consciousness and abnormal behavior. Human brain is composed of more than 10 to the power 10 neurons, each of which receives electrical impulses (known as action potentials) from others neurons via synapses and sends electrical impulses via a sing output line to a similar (the axon) number of neurons (Shatz 1981). When neuronal networks are active, they produce a change in voltage potential, which can be captured by an electroencephalogram (EEG). The EEG recordings represent the time series that match up to neurological activity as a function of time. The structure of EEG recordings represent the inter activities among the groups of neurons. Many investigators have applied nonlinear dynamical methods in a broad range of medical applications. More recent nonlinear dynamical methods have shown the abilities to explain some underlining mechanisms of brain functions (Babloyantz and Destexhe 1986, 1987; Babloyantz 1988; Babloyantz et al. 1985). Roschke and Aldenhoff (1991); Fell et al. (1993) have reported the chaotic behavior of the human EEG during sleep changed as the sleep stage changed (Iasemidis and Sackellares 1991; Iasemidis and Sackellares 1996). Iasemidis and Sackellares et al. have shown that the nonlinear dynamical methods have the abilities to find out the abnormal activity in EEG recordings from epilepsy patients (Iasemidis and Sackellares 1991; Iasemidis and Sackellares 1996; Iasemidis et al. 1990, 1996).

In this present study, we used nonlinear dynamical measurements to investigate the behavior of underlining dynamical complexity of EEG recordings from patients with epilepsy. More particularly, we sought to evaluate the degree of underlining dynamical complexity prior to initiation of seizure onsets. Several previous studies have shown the presences of nonlinearity in the EEG recordings acquired from epilepsy patients. Casdagli et al. (1996) reported the presence of nonlinearity in the invasive EEG recordings from epileptic regions of patients. Palus (1996); Thelier and Rapp (1996) have also shown the weak nonlinearities in the EEG recordings from normal human volunteers using surrogate data methods.

It is known that a dynamical system with d degree of freedom may evolve on a manifold with a lower dimension, so that only portions of the total number of degree of freedom are actually active. For a simple system with limit cycles, it is obvious that time-delay embedding produce an equivalent reconstruction of the true state. According to embedding theorem from Whitney (1936), an arbitrary D-dimension curved space can be mapped into a Cartesian (rectangular) space of $2D + 1$ dimensions without having any self intersections, hence satisfying the uniqueness condition for an embedding. Sauer et al. (1991) generalized *Whitney's* theorem to fractural attractors with dimension D_f and showed the embedding space only need to have a dimension greater than $2D_f$. Although it is possible for a fractal to be embedded in another fractal, we only consider the integer embeddings. *Takens'* delay embedding theorem (Takens 1981) also provided that the time lagged variables constitute an adequate embedding provided the measured variables is smooth and couples to all the variables, and number of time lags is at least $2D + 1$.

For the above reasons, we employed a method proposed by Cao (1997) to estimate the minimum embedding dimension of EEG time series. Like some other exiting methods, Cao's method is also under the concepts of "false-nearest-neighbors" (Kennel et al. 1992). The "false-nearest-neighbors" utilized on the fact that if the reconstruction space has not enough dimensions, the reconstruction will perform a projection, and hence will not be an embedding of the desired system. As a of result of giving a to low embedding dimension while processing the embedding procedure, two points which is far away in the true state space will be mapped into close neighbor in the reconstruction space. These are then the "false neighbors". Cao's method overcomes the drawbacks of the exiting algorithms. It does not require huge amount of data points, is not subjective and it is not time-consuming find the optimal minimum embedding dimension. The EEG recordings was divided into non-overlapping single electrode segments of 10.24 s duration, each of which was estimated for the minimum embedding dimension. Under the assumption "the EEG recordings within each 10.24 s duration was approximately stationary (Iasemidis et al. 1993)", we evaluated the underlining dynamical behavior by looking at the minimum embedding dimension over time.

The remaining of this paper is organized as follows. In Sects. 2 and 3, we describe the data information and explain the algorithms for the minimum embedding dimension estimation. The results from two patients with a total number of six temporal lobe epilepsy (TLE) are given in Sect. 4. In Sect. 5, we discuss the results of our findings with respect the use of this algorithm and the function of nonlinear dynamical measurements in the area of seizure control.

2 Data information

Electrographic (EEG) recordings from bilaterally placed depth and subdural electrodes in patients with medically refractory partial seizures of mesial temporal origin were analyzed in this study (Casdagli et al. 1997). A typical epileptic electrode montage for such recordings is shown in Fig. 1. The EEG recording data for epilepsy patients were obtained as part of pre-surgical clinical evaluation. They had been obtained using a Nicolet BMSI 4000 and 5000 recording system, using s 0.1 Hz highpass and a 70 Hz low pass filter. Each record included a total of 28 to 32 intracranial electrodes (8 subdural and 6 hippocampal depth electrodes for each cerebral hemisphere). Prior to storage, the signals were sampled at 200 Hz using an analog to digital converter with 10 bits quantization. The recordings were stored digitally onto high fidelity video type. Two epilepsy patients (see Table 1) were included in this study.

3 Methods

3.1 Nonstationarity

Nonstationarity is an inhered problem for analyzing biological time series analysis. As result of nonstationarity in a measured biological time series, no invariant measures would able to carry out. Nonstationarity will also cause errors for many measurements to invalid on the assumption and produce bias results. To avoid the above situations, one can try to remove the nonstationarity by using linear filter (i.e. differencing, bleaching or spectral filtering) or dividing time series into a number of shorter windows and assume the underlining dynamics to be approximately statistically stationary within each small divided window. In this study, EEG recordings were divided into non-overlapping segmentation of 10.24 s duration to deal with inhered nonstationarity property in EEG. The same divided method has also been previous used by Iasemidis et al. (1993). Such segmentation technique is usually applied for biological time series, by performing calculation on each 10.24 s windows, the changes of the dynamical properties over time could be detected.

3.2 Proper time delay

We used the mutual information function to estimate the proper time delay between successive components in delay vectors. In theory, the time delay used for time delay vector reconstruction is not the subject of the embedding theorem. Since the data are assumed to have infinite precision, from mathematical point of view delay time can be chosen arbitrary. On the other hand, it is essential to have a good estimation for proper time delay when dealing with none artificial data. For none artificial data, the time delay parameter can affect the dynamical properties under studying, if time delay is very large, the different coordinates may be almost uncorrelated. In this case, the attractor may become very complicated, even if the underlying "true" attractor is simple. If delay is too small, there is almost no difference between the different components between delay vectors, such that all points are accumulated around the bisectrix in the embedding space.

Therefore, it is suggested to look for the first minimum of the time delay mutual information Fraser and Swinney (1986). The concept of mutual information is given as below Martinerie et al. (1992). Consider system S and Q consisting of discrete sets of possible messages $\{s_1, s_2, \ldots, s_n\}$ and $\{q_1, q_2, \ldots, q_n$ with associated probabilities $\{P_s(s_1), \ldots, P_s(S_n)\}$ and $\{P_q(q_1), \ldots, P_q(q_m)\}$. The }entropy $H(S)$ is the average amount of information gained from a measurement of S

$$H(S) = -\sum P_s(s_i)\log_2 P(s_i) \, .H(Q)$$

is defined at the same notation as *H(S)*.

The mutual information of S and Q system is denoted by $I(Q,S)$. Given a measurement of s, $I(Q,S)$ is the number of bits of q on average, that can be predicated,

$$I(Q,S) = H(Q) + H(S) - H(S,Q),$$

where $H(Q)$ and $H(S)$ are entropies of system Q and system S, respectively. $H(S,Q)$ is the join entropy function. $H(S,Q)$ is denoted the average amount of information gained from measuring (s, q) pairs, where the joint-probability distribution, denoted $P_{sq}(s_i; q_j)$, is the probability that $s = s_i$ and $q = q_i$,

$$H(S,Q) = -\sum_i^n \sum_j^m P_{sq}\left(s_i,q_j\right)\log_2 P_{sq}(s_i,q_i) \, .$$

Suppose a variable v is investigated by being sampled with sampling interval T_s. Let such process be the context of system S and system Q, let s be the measurement of v at time t, and let q be the measurement at time $t + T_s$. Using these measurement to define systems S and Q, mutual information $I(Q,S)$ can be calculated. Thus, mutual information becomes a function of T_s. For this problem, mutual information will be the number of bits of $v(t + T_s)$ that can be predicated, on average, when $v(t)$ is known. One wants to pick T_s should be chosen so that $v(t + T_s)$ is as unpredictable as possible. Maximum unpredictability occurs at minimum of predictability; that is, at the minimum in the mutual information. Because of the exponential divergence of chaotic trajectories, the first local minimum of $I(Q,S)$, rather than some subsequent minimum, should probably be chosen for the sampling interval T_s.

3.3 The minimum embedding dimension

Dynamical systems processing d degree of freedom which may choose to proceed on a manifold of much lower dimension, so that only small portions of the degrees of freedom are actually active. In such case it is useful to estimate the behaviors of degrees of freedom over a period of time, and it is obvious that this information can be obtained from that dimension of attractor from the corresponding system. If one chooses the embedding dimension too low this results in points that are far apart in the original phase space being moved closer together in the reconstruction space. Taken's delay embedding theorem (Takens 1981) states that a pseudo-state space can be reconstructed from infinite noiseless time series (when one choose $d > 2d_A$) is often been used when reconstructing the delay vector. There are several classical algorithms (Grassberger and Procaccia 1983; Kennel et al. 1992; Broomhead and King 1986) used to obtain the minimum embedding dimension. The classical approaches usually require huge computation power and vast among of data. Another limitation of these algorithms is that they usually subjective to different types of data. We evaluated the minimum embedding dimension of the attractors from the EEG by using Cao's method (Cao 1997). The notions here followed "Practical method for determining the minimum embedding dimension of a scalar time series" (Cao 1997). Suppose that we have a time series $\{x_1, x_2, x_3, \ldots, x_N\}$. By applying the method of delay we obtain the time delay vector. The time-delay vector is as follows:

$$y_i(d) = (x_i, x_i+\tau, \ldots, x_i + (d-1)\tau), \quad i=1,2,\ldots,N-(d-1)\tau$$

where d is the embedding dimension and τ is the time-delay and $y_i(d)$ means the ith reconstructed vector with embedding dimension d. Similar to the idea of the false neighbor methods [ ], defining

$$a(i,d) = \frac{\|y_i(d+1) - y_{n(i,d)}(d+1)\|}{\|y_i(d) - y_{n(i,d)}(d)\|}, \quad i=1,2,\ldots,N-d\tau$$

where $\|\cdot\|$ is some measurement of Euclidian distance and is given in this paper by maximum norm. Define the mean value of all $a(i, d)$'s as

$$E(d) = \frac{1}{N-d\tau}\sum_{i=1}^{N-d\tau} a(i,d).$$

$E(d)$ is dependent only on the dimension d and the time delay τ. The minimum embedding dimension is founded when $E1(d) = E(d+1)/E(d)$ saturated when d is larger than some value d_0 if the time series comes from an attractor. The value $d_0 + 1$ is the estimated minimum embedding dimension.

4 Data analysis

The first step in the data analysis was to divide the EEG data into non-overlapping windows of 10.24 seconds in duration for nonstationarity purposes. This procedure was to ensure that the underlining dynamical properties were approximately stationary. For each divided window, the first step of estimating the minimum embedding dimension is to construct the delay coordinates using method of delay proposed by Takens (1981). The time delay τ was obtained from the first local minimum of the mutual information function. We used these time delay vectors as inputs to Cao's method for the minimum embedding dimension estimation. The minimum embedding dimension was calculated over time for EEG recordings with 29 electrodes at six brain regions (RTD, RST, ROF, LTD, LST, and LOF) from epilepsy patients. Each brain region contains 4-6 electrodes; the average of the minimum embedding dimension d_a is taken as representation to the underlining brain dynamics. We shall study the minimum embedding dimension in the following three different time periods: *Inter-Ictal, lctal and Post-Ictal*. These three different time periods are defined as follows:

1. *Inter-Ictal* period: 1 hour data length and 1 hour away before seizure onset
2. *Ictal* period: 2 minutes data length after seizure onset
3. *Post-Ictal* period: 1 hour data length and 1 hour after the ictal period

Figures 2, 3, 4, 5 and 6 exhibits the minimum embedding dimension over time corresponding five seizures. One can observe that behavior of the average minimum embedding dimension over time from six recording regions. The minimum embedding dimension behaved stable during the *Inter-Ictal* period. In other words, the underlying degree of freedomly is uniformly distributed over the *Inter-Ictal* period in the EEG recordings. The results indicated that the lowest values of the minimum embedding dimension were observed from the epileptic zone during *Inter-Ictal* period (the RST electrodes in Figs. 2, 3, and 4; the LTD electrodes in Figs. 5 and 6). The complexity of the EEG recordings from the epileptic region is lower than that from the normal regions. The values of the minimum embedding dimension from all brain regions start decreasing and converging to a lower value as the patient proceed from *Inter-Ictal* to *Ictal* period. The underlining dynamical changes before entering *Ictal* period were consistently detected by our algorithm.

5 Discussion

We study the underlining dynamical behaviors in the EEG recordings by estimating the minimum embedding dimension. The algorithm we use for the minimum embedding estimation is faster and requires less data points to obtain accurate results. It is computationally efficient and certainly less time consuming compared to some classical procedures for estimating embedding dimension estimation. The drawback of employing this algorithm is that it does not adopt with the noise in the EEG recordings. In the cases 2 and 3, after the seizure onset the decreases in the minimum embedding dimension was due to artificial noise in the EEG recordings. This drawback can certainly be overcome by carefully exam the EEG recordings before the minimum embedding dimension estimation. Our results are compatible with the findings about the nature of transitions to Ictal period in invasive EEG recordings from patients with seizures of mesial temporal origin. Iasemidis and Sackellares et al., have also reported that the order of the EEG recordings start decreasing when that period of the patient is close to Ictal period. The complexity of underlining dynamical system drops lead to the order of the EEG recordings increase. The decrease and converge in the minimum embedding dimension can be used to detect seizure onset by developing more sophisticated mechanism. Further studies on a larger sample of patients to validate these results are warranted. Success of this study will provide more much helpful information to guide patients and epileptologists to improve the likelihood of successful seizure control.

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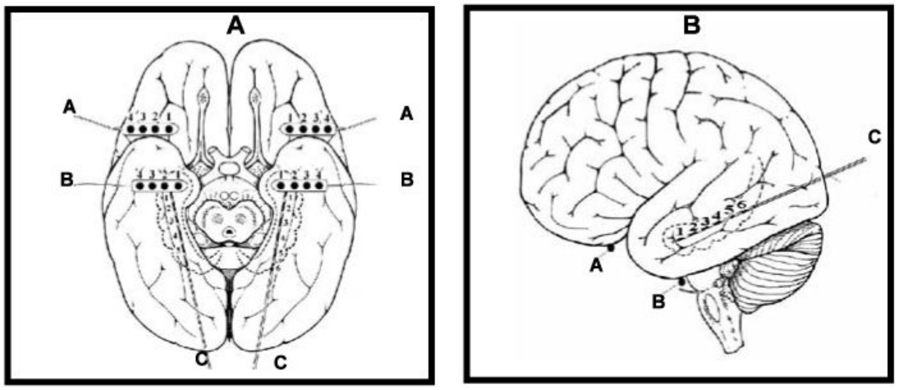

Fig. 1.

Electrode placement. **A** Inferior transverse and **B** lateral views of the brain, illustrating approximate depth and subdural electrode placement for EEG recordings are depicted. Subdural electrode srips are placed over the left orbitfrontal (LOF), right orbitofrontal (ROF), left subtemporal (LST), and right subtemporal (RST) cortex. Depth electrodes are placed in the left temporal depth (LTD) and right temporal depth (RTD) to record hippocampal activity

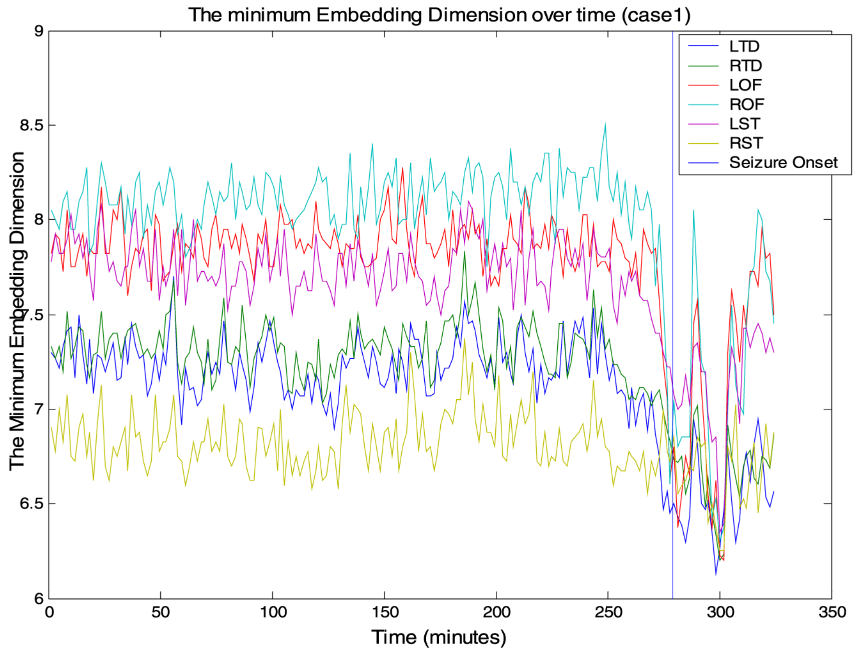

Fig. 2.
The minimum embedding dimension profiles over the first seizure of Patient 1 (case 1) from all six brain areas are shown. Each profile is an average over all electrodes in the area

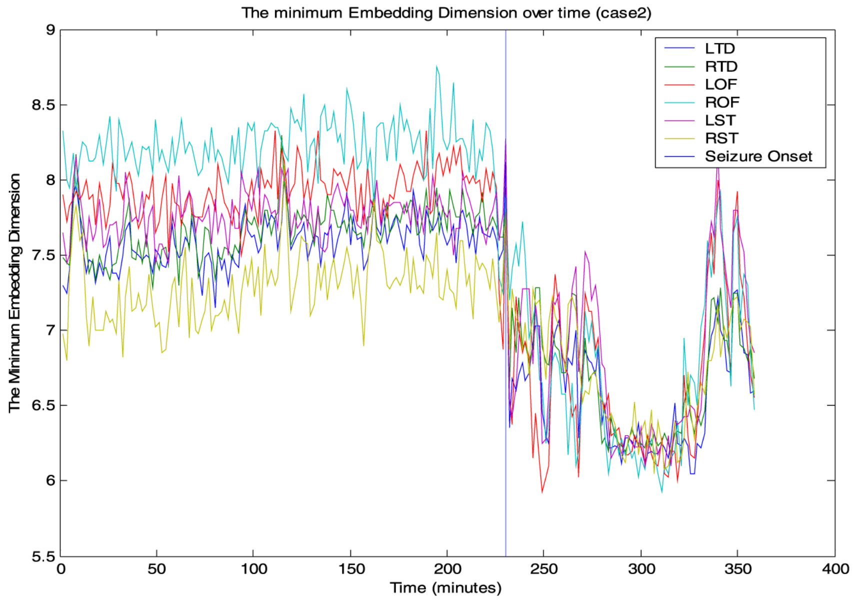

Fig. 3.

The minimum embedding dimension profiles over the second seizure of Patient 1 (case 2) from all six areas of the brain are shown. Each profile is an average over all electrodes in the area

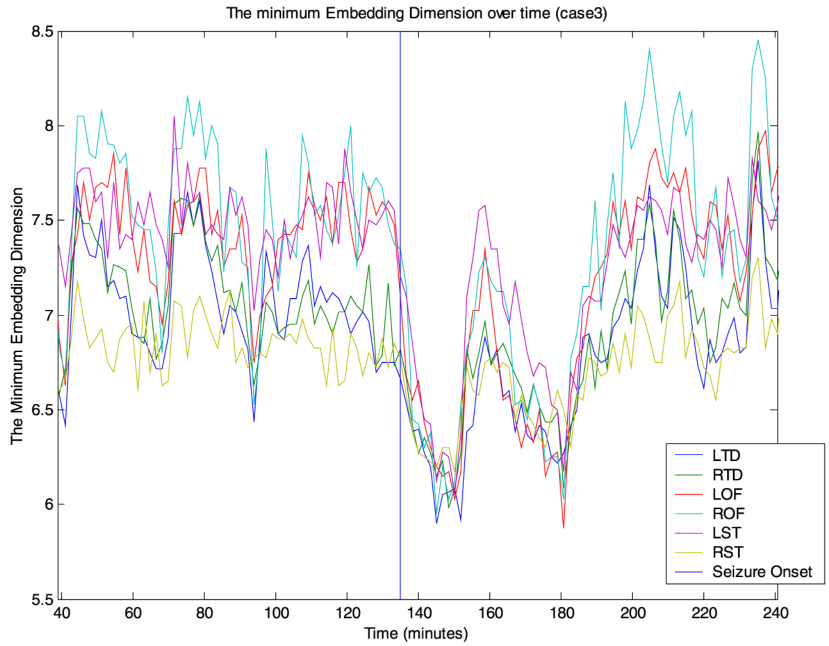

Fig. 4.
The minimum embedding dimension profiles over the third seizure of Patient 1 (case 3) from all six areas of the brain are shown. Each profile is an average over all electrodes in the area

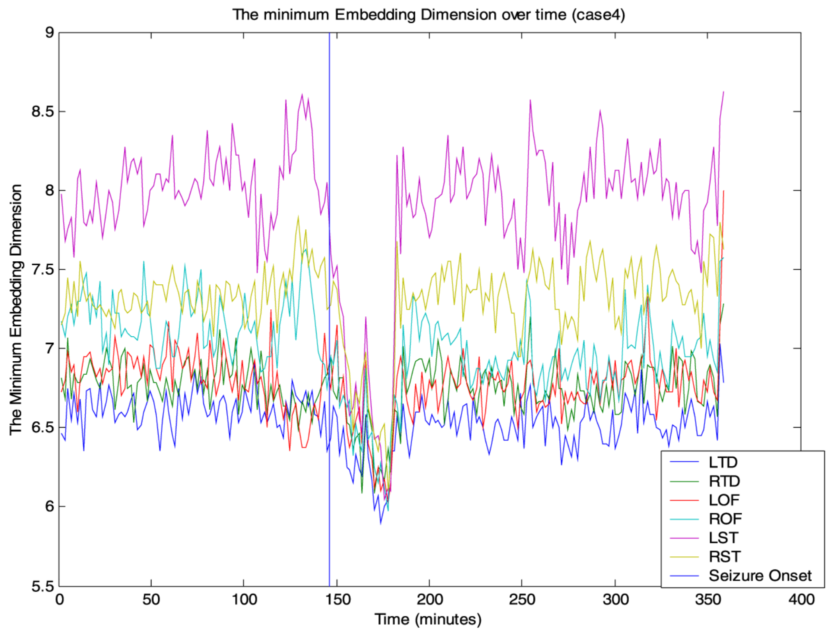

Fig. 5.

The minimum embedding dimension profiles over the first seizure of Patient 2 (case 4) from all six areas of the brain are shown. Each profile is an average over all electrodes in the area

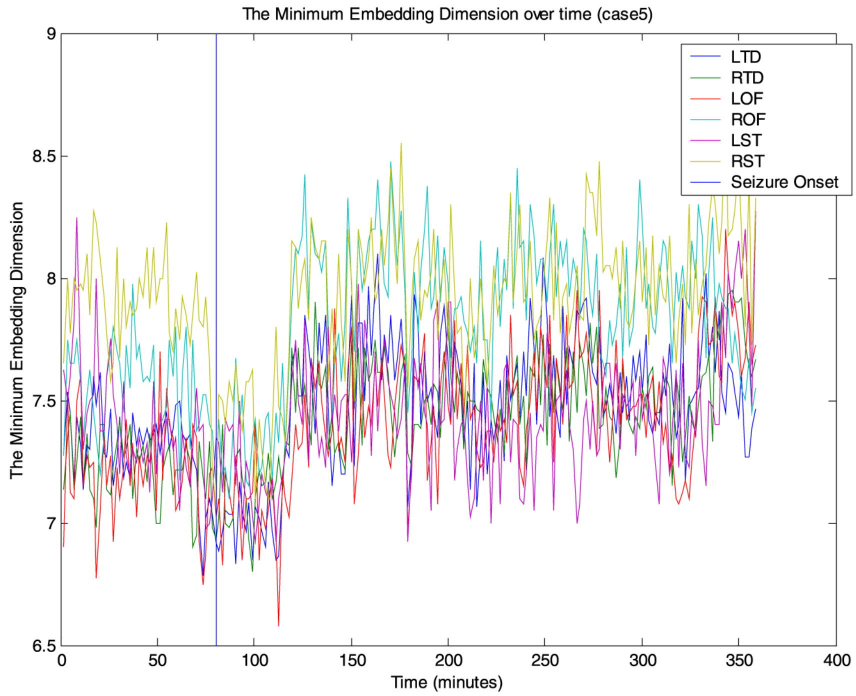

Fig. 6.

The minimum embedding dimension profiles over the first seizure of Patient 2 (case 5) from all six areas of the brain are shown. Each profile is an average over all electrodes in the area

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Table 1

Patient information

Patient ID	Age	M/F	No. electrodes	Focus area	Total time	Number of SZ
P1	19	M	29	RTD	20h 37m 05s	3
P2	33	M	29	LTD	9h 43m 57s	2