Clinical Neurophysiology 125 (2014) 1104-1111

Contents lists available at ScienceDirect

Clinical Neurophysiology

journal homepage: www.elsevier.com/locate/clinph

Epileptic seizure prediction using phase synchronization based on bivariate empirical mode decomposition



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ARTICLE INFO

Article history: Accepted 24 September 2013 Available online 15 November 2013

Keywords: Seizure prediction Bivariate empirical mode decomposition Phase synchronization Electroencephalogram

HIGHLIGHTS

- Phase synchronization information of intrinsic mode functions extracted by bivariate empirical mode decomposition was used to perform seizure prediction.
- Both the increase and the decrease of phase synchronization can be found before seizure onset.
- The proposed method achieved superior performance than the corresponding random predictor, which demonstrated its effectiveness for seizure prediction.

ABSTRACT

Objective: Epilepsy is a common neurological disorder with unpredictability. An effective algorithm for seizure prediction is important for the patients with refractory epilepsy.

Methods: We proposed a seizure prediction method based on the phase synchronization information of neuronal electrical activities. Firstly, the instantaneous phase of the intracranial electroencephalograph (EEG) recordings was detected by the combination of bivariate empirical mode decomposition (BEMD) and Hilbert transformation. Then, the phase information was used to calculate the mean phase coherence (MPC) as a measure of phase coupling strength between different channels of EEG recordings. In the end, the preictal changes of MPC time courses were used to raise the seizure alarms. We compared the proposed method with other existing methods to further investigate its effectiveness.

Results: Both the increase and the decrease of phase synchronization were found prior to seizure onset. Our results indicated that the proposed method had the best performance among three predictors.

Conclusions: The proposed algorithm can effectively extract the phase synchrony changes prior to the seizure onset and contribute to the application of the seizure prediction.

Significance: Phase synchronization analysis based on the BEMD method may be a useful algorithm for clinical application in epileptic prediction.

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1. Introduction

Epilepsy is one of the most common neurological disorders which have the sudden and apparently unpredictable nature. About 75% of the patients can achieve effective seizure control from anticonvulsive medication or resective surgery. In addition, the remaining 25% of patients have still no sufficient treatment nowadays (Mormann et al., 2007). The seizure prediction can

significantly improve the possibilities of epilepsy therapy and further enhance the life quality of epilepsy patients. In general, the occurrence of seizures could evolve in two different ways (Silva et al., 2003). One is the focal epilepsy with dynamic changes in electroencephalogram (EEG) before seizure onset. The other is the primary generalized epilepsy without any dynamic changes before seizure onset. Usually, the seizure prediction is only possible to be carried out for the first situation.

Many attempts to extract the seizure precursors from the scalp EEG recordings have been made during the past several decades. Early studies focused on the linear approaches, such as the autoregressive modeling (Rogowski et al., 1981; Salant et al., 1998) and pattern detection by analyzing spike occurrence (Gotman et al., 1982; Siegel et al., 1982). In the 1980s, the nonlinear approaches



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were proposed to describe the dynamic characteristics of EEG signals for epilepsy patients. These methods included the largest Lyapunov exponent (Lasemidis et al., 1990), the correlation density (Martinerie et al., 1998), the dynamical similarity index (Quyen et al., 1999; Navarro et al., 2002), etc. However, most of these nonlinear methods were questioned when they were carried out on the extensive database (Lai et al., 2003; Mcsharry et al., 2003; Winterhalder et al., 2003).

Recently, many investigators made an attempt to predict the occurrence of seizures by characterizing the interaction of different brain regions because the seizure was considered from the abnormal synchronization of different neurons. Mormann et al. (2000) used the Hilbert transform to calculate the mean phase coherence (MPC) as a measure for phase synchronization of EEG signals. Subsequently, they reported that seizure onsets could be predicted by a decrease of phase synchrony of EEG signals for epilepsy patients (Mormann et al., 2003). However, recent studies indicated that the performance of a random predictor could be comparable with that of the original Hilbert-based MPC method (OHM) for seizure prediction (Kuhlmann et al., 2010; Wang et al., 2011). This may be due to the fact that the EEG signals are the summation of brain neuronal electrical activity around the recording electrode (Fine et al., 2010), which results in the multi-component nature of the EEG signals. Nevertheless, the OHM method is only suitable for mono-component signals because Hilbert transform is actually a filter with unit gain for every frequency component (Rosenblum et al., 1996).

The empirical mode decomposition (EMD) method can adaptively decompose a multi-component signal into a series of signal oscillators termed as intrinsic mode functions (IMFs) (Huang et al., 1998). This method has widely applied to the electrophysiological signal processing (Li et al., 2012; Pal and Mitra, 2012). However, the EMD method makes it difficult to calculate the exact withinfrequency phase synchronization because the IMFs from different time series may correspond to different frequency bands (Looney et al., 2009). In order to remove this limitation, (Rilling et al., 2007) extended the EMD method to the bivariate empirical mode decomposition (BEMD) method which can simultaneously decompose two channels of signals into several paired IMFs with the same frequency bands.

In order to improve the performance of the OHM method, we proposed to combine the BEMD and the Hilbert-based MPC method (BHM) to extract the phase synchronization information of the EEG signals for seizure prediction in this study. Firstly, the instantaneous phase was obtained by combining the BEMD method and the Hilbert transformation. Then, the MPC was calculated as a measure of phase coupling strength. Finally, the preictal changes of the MPC were employed to predict the occurrence of seizures. In addition, the effectiveness of the proposed algorithm was evaluated by comparing with other existing methods of seizure prediction. This paper was organized as follows: in Section 2, methodologies used in this study were briefly introduced; in Section 3, the experimental results using the proposed method were presented and a comparative analysis with other methods was provided. The discussion and conclusion were drawn in the final section.

2. Methods

2.1. Database and preprocessing

In this study, the Freiburg EEG database (http://epilepsy.unifreiburg.de) was used to test the proposed seizure prediction algorithm. The EEG data of this dataset were recorded at the Epilepsy Center of the University Hospital of Freiburg during invasive presurgical epilepsy monitoring (Aschenbrenner-Scheibe et al., 2003). The sampling rate of the signals was 256 Hz. A certified epileptologist took visual inspection to select the six contacts from all implanted grid, strip and depth electrodes for further data analysis. Specifically, three intra-focal contacts (electrode contacts 1, 2, and 3) were chosen from the epileptogenic zone involved in early ictal activities. The remaining extra-focal contacts (electrode contacts 4, 5, and 6) were from areas not involved or latest involved during seizure spread. The detail information about electrode contacts could be found from the Freiburg EEG database.

The intracranial EEG recordings of 21 patients were available in this database and the number of seizures of different patients ranged from 2 to 6. Ten patients with 5 seizures were chosen for further analysis. Details on patient characteristics and EEG data are given in Table 1. The 50 min preictal data and at least 20 h (22.2 ± 1.90) interictal data were obtained for each patient. The interictal period was defined as at least 1 h before or after a seizure. In order to reduce the effects of power frequency interference and artifact noises, the original EEG data were preprocessed by a 50 Hz notch filter and the whole time blocks (about 1 h) with artifacts were removed.

2.2. Analysis paradigm

The analysis flowchart of seizure prediction algorithm is illustrated in Fig. 1. It consists of five steps: window segmentation, BEMD, MPC calculation, feature selection and seizure prediction. Firstly, the sliding window technique described in (Mormann et al., 2000) was used to segment EEG recordings here. The 5120 samples (20 s) were allocated to each analysis window with a 20% overlap. Secondly, the IMFs were obtained by the BEMD method for every possible combination of two different EEG recording contacts. Then, there were totally 75 pairs of IMFs for each analysis window. Thirdly, the MPC was calculated for each pair of IMFs and totally 75 MPC values were obtained for each analysis window. Fourthly, the MPC time courses with obvious preictal changes were selected as the features of performing seizure prediction. Finally, a threshold crossing of the selected MPC time series was used to raise the seizure alarm.

2.2.1. Bivariate empirical mode decomposition

The BEMD method can be used to adaptively filter two channels of EEG signals into oscillations with different frequency components simultaneously. This approach can prevent inappropriate frequency components from disturbing the extraction of the phase information of signals. According to the BEMD method, bivariate signals can be seen as fast rotations (local details) superimposed on slow rotations (local trend) (Rilling et al., 2007). In order to separate slow rotations from fast rotations, an envelope should be defined as a 3-dimensional tube tightly enclosing two signals. As the

Table 1	
Summary of patient characteristics and EEG data for all patients.	

Patient No.	Seizure origin	Used interictal duration (h)	Number of seizures
3	Frontal	20.9	5
4	Temporal	22.9	5
5	Frontal	20.9	5
9	Temporal/ occipital	20.0	5
10	Temporal	24.4	5
16	Temporal	20.9	5
17	Temporal	20.0	5
18	Frontal	24.8	5
20	Temporal/ parietal	24.5	5
21	Temporal	22.8	5

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