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A low computation cost method for seizure prediction

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Summary The dynamic changes of electroencephalograph (EEG) signals in the period prior to epileptic seizures play a major role in the seizure prediction. This paper proposes a low computation seizure prediction algorithm that combines a fractal dimension with a machine learning algorithm.

The presented seizure prediction algorithm extracts the Higuchi fractal dimension (HFD) of EEG signals as features to classify the patient's preictal or interictal state with Bayesian linear discriminant analysis (BLDA) as a classifier. The outputs of BLDA are smoothed by a Kalman filter for reducing possible sporadic and isolated false alarms and then the final prediction results are produced using a thresholding procedure. The algorithm was evaluated on the intracranial EEG recordings of 21 patients in the Freiburg EEG database.

For seizure occurrence period of 30 min and 50 min, our algorithm obtained an average sensitivity of 86.95% and 89.33%, an average false prediction rate of 0.20/h, and an average prediction time of 24.47 min and 39.39 min, respectively. The results confirm that the changes of HFD can serve as a precursor of ictal activities and be used for distinguishing between interictal and preictal epochs. Both HFD and BLDA classifier have a low computational complexity. All of these make the proposed algorithm suitable for real-time seizure prediction.

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Introduction

Epilepsy affects approximately 1% of the word's population by the sudden and recurrent occurrence of seizures. The epileptic seizures arise from abnormally excessive neuronal spontaneous, synchronized discharges in the cerebral cortex, and there are a significant number of epileptic patients at risk of serious injury or death. Therefore, the ability to effectively predict impending seizures would significantly improve the quality of life of epileptic patients, and provide novel methods for the prevention and treatment of epilepsy. A seizure warning device would augment the therapeutic options or allow behavioral adjustments of those epilepsy patients. Additionally, various intervention systems could be applied to suppress seizures in advance of their clinical manifestation, e.g., by delivering short-acting antiepileptic drugs or by applying electric stimulation (Schelter, 2007).

Research on seizure prediction through electroencephalograph (EEG) recordings began in the 1970s. Since then, a large number of studies have been carried out and great efforts have been spent on seizure prediction through EEG monitoring. It has long been observed that the transition from the interictal state (far from seizures) to the ictal state (seizure) is not sudden and may be preceded from minutes to hours by clinical, metabolic or electrical changes, that is there exists a preictal state (Lehnertz et al., 2001).

Most current seizure prediction approaches can be summarized into two steps. The first is extracting linear or nonlinear measurements of scalp or intracranial EEG signals recorded from epileptic patients. The second is classifying them into a preictal or interictal state using statistical analysis or other machine learning techniques (Mirowski et al., 2009). Among these measures, those taken from the theory of chaotic dynamics, including the largest Lyapunov exponent (Iasemidis et al., 1990), correlation dimension (Lehnertz and Elger, 1998), dynamic similarity index (Le Van Quyen et al., 2001), entropy (Drongelen et al., 2003; Li et al., 2007), and phase synchronization (Mormann et al., 2003; Kuhlmann et al., 2010), have shown higher seizure predictability power than linear measurements such as statistical moments, power spectra features and so on (Mormann et al., 2007). However, to calculate much of these nonlinear measurements, phase space reconstruction is required which increases the algorithm complexity and calculation burden significantly. A nonlinear measurement which can be calculated directly in the time domain is desired in a real-time seizure prediction system, and Higuchi fractal dimension (HFD) is such an appropriate measurement to quantify signal's dimensional complexity (Higuchi, 1988), which can be used to study changes in the dynamical behavior of the brain, due to the following reasons. Though many algorithms are available to compute FD in the time domain, like those proposed by Katz (1988) and Petrosian (1995), HFD provides more accurate estimation of the fractal dimension than the methods of Katz and, compared with Petrosian's algorithm, HFD does not depend on a binary sequence and it is less sensitive to noise in many cases (Esteller et al., 2001). HFD has already been used to quantify the complexity of EEG recordings (Khoa et al., 2012; Schneider et al., 2009; Bao et al., 2008). In this paper, HFD is applied to characterize the nonlinear dynamical properties underlying EEG signals for seizure prediction. A good classifier is essential for an excellent seizure prediction method. Bayesian linear discriminant analysis (BLDA) algorithm has shown its good performance for binary classification in the area of brain—computer interface (Hoffmann et al., 2008), due to the fact that it avoids over-fitting phenomenon and time-consuming cross-validation. In this work, this method is employed to classify the HFD features of intracranial EEG recordings in the preictal and interictal state.

Material and methods

EEG dataset and preprocessing

The EEG recordings used in this work came from the Epilepsy Center of the University Hospital of Freiburg, Germany. This database contains intracranial EEG signals of 21 patients recorded during an invasive pre-surgical epilepsy monitoring. These EEG data were obtained using a Neurofile NT digital video EEG system with 128 channels, 256 Hz sampling rate, and a 16-bit analogue-to-digital converter. Six contacts of all implanted grid, strip, and depth electrodes were selected before any analyses by visual inspection of the raw data by a certified epileptologist (Schelter et al., 2006). Three are focal channels (located near the epileptic focus) and three extra-focal.

The EEG recordings for each patient contain separate ictal and interictal datasets. The ictal dataset contains between 2 and 5 epileptic seizures notated by the experienced epileptologists and at least 50 min of preictal data for most seizures. The onset and offset times of seizures had been previously determined by the experienced epileptologists based on identification of epileptic patterns preceding clinical manifestation of seizures in IEEG recordings (Aarabi and He, 2012). Approximate 24 h interictal EEG recordings without seizure activity are available in interictal datasets.

Only three focal channels of 21 patients were chosen for seizure prediction in this work. Firstly the moving-window technique was used to split long term EEG recordings into 4s epochs without overlap. Then the Chebyshev bandpass digital filters were used to limit the frequency band of EEG epochs to 0.5—30 Hz.

Extraction of Higuchi fractal dimension

As the reconstruction of the attractor phase space is not necessary, the calculation of Higuchi fractal dimension is simpler and faster than other classical measures derived from chaos theory. A short introduction to the computation of HFD is included in Appendix A.

For each epoch, the HFD of the EEG segment from each of the three selected channels were calculated and stacked into a three dimensional feature vector.

Machine learning classification

Once features had been extracted from EEG recordings, classification as preictal or interictal was carried out. The classifier used in this work was Bayesian linear discriminant analysis (Hoffmann et al., 2008). As an extension of