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Seizure detection method based on fractal dimension and gradient boosting

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ABSTRACT

Automatic seizure detection technology is necessary and crucial for the long-term electroencephalography (EEG) monitoring of patients with epilepsy. This article presents a patient-specific method for the detection of epileptic seizures. The fractal dimensions of preprocessed multichannel EEG were firstly estimated using a *k*-nearest neighbor algorithm. Then, the feature vector constructed for each epoch was fed into a trained gradient boosting classifier. After a series of postprocessing, including smoothing, threshold processing, collar operation, and union of seizure detections in a short time interval, a binary decision was made to determine whether the epoch belonged to seizure status or not. Both the epoch-based and event-based assessments were used for the performance evaluation of this method on the EEG data of 21 patients from the Freiburg dataset. An average epoch-based sensitivity of 91.01% and a specificity of 95.77% were achieved. For the event-based assessment, this method obtained an average sensitivity of 94.05%, with a false detection rate of 0.27/h.

1. Introduction

Epilepsy is a common neurological disorder that affects approximately 1% of the world's population. Epileptic seizures are clinical manifestation of abnormal and excessive neuronal discharges in the brain and can result in disturbance of consciousness and sudden loss of motor control [1]. In epilepsy diagnosis, such as assessment of seizure type and frequency, localization of the epileptogenic region in the brain, and EEG investigations for epilepsy surgery, long-term EEG monitoring is useful and mandatory in epilepsy surgery centers and intensive care units [2]. Though long-term EEG recordings can be visually inspected by highly trained clinicians, it is a tedious and time-consuming process. Therefore, automatic seizure detection technology can be a valuable aid to neurologists in analyzing EEG recordings.

One of the first approaches for seizure detection was introduced by Gotman [3], where individual EEG signals were broken into half waves and three different measures (average amplitude, average duration, and coefficient of variation) were calculated for each epoch. Then, seizure detection was obtained by comparing these measures with some empirically predefined thresholds. The method was later improved by Gotman [4] and Qu [5]. After that, approaches for seizure detection based on pattern recognition and machine learning theory have been proposed. Qu and Gotman designed a patient-specific algorithm to detect seizure onsets, where a modified nearest neighbor classifier was used after extracting five features from the time and frequency domains [6]. In the seizure warning system for intracerebral EEG introduced by Grewal and Gotman [7], the seizure probability of a section of EEG was calculated using Bayesian formulation. In addition, artificial neural network [8–10] and support vector machine [11–13] were widely used to build automatic seizure detection algorithms. The usage of pattern recognition and machine learning theory in seizure detection is premised on the extraction of representative features from epileptic EEG recordings. Features, extracted in time domain [14,15], frequency domain [16], and time-frequency domain like wavelet transform [17–19] and Hilbert–Huang transform [20], have been used in most seizure detection algorithms. At present, a growing number of studies have investigated the nonlinear features in the EEG as well, such as the largest Lyapunov exponent [21], correlation dimension [22], and entropies [23,24]. The functions of the brain at the microscopic level, i.e., the interplay of neurons, is extremely nonlinear in nature since the dynamic behavior of individual neurons is decided by threshold and saturation phenomena [25]. Electroencephalography signals recorded from the brain also have significant nonlinearity because of the close relationship with physiological and pathophysiological functions of the brain. Hence, instead of the traditional linear methods, nonlinear dynamic analysis methods may better suit the feature extraction of EEG signals.

In this study, we systematically describe an automatic patient-specific seizure detection method, which extracts the nonlinear feature, fractal dimension (FD) based on the *k*-nearest neighbor algorithm, and discriminates the feature vector of an epoch for seizure or nonseizure

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status using a gradient boosting algorithm. Fractal dimension is a powerful tool for transient detection and also a measure of the dimensional complexity of fractal objects. Fractal dimension can be calculated from a set of points using several diverse methods that differ in accuracy, sensitivity to the number of points used, and the time required for computation [26]. In contrast to the box-counting method, in which FD estimation considers the variation of mass inside fixed-size cubes, the k-nearest neighbor algorithm belongs to fixed-mass algorithms, according to which FD estimation is based on the scaling of the sizes of cubes so that they contain the same number of points (mass) [26]. The k-nearest neighbor algorithm has been previously applied for the estimation of the fractal dimension of strange attractors [27], gray-level images [28], and scalp EEG data [29]. Compared with other well-known estimators of the fractal dimension, such as box-counting method [30], correlation algorithm [26], Katz's algorithm [31], and Higuchi's algorithm [32], it has been proven superior in terms of accuracy, dynamic range, and computational time. Gradient boosting used as a classifier in this work can build one strong classifier from many weak classifiers [33,34]. For its conceptual simplicity, gradient boosting has been used in many research domains, such as remotely sensed imagery [35] and brain–computer interface [36].

The organization of the succeeding sections of this paper is as follows. The proposed seizure detection method and the EEG data analyzed are described in Section 2. Results are presented in Section 3. Section 4 is devoted to discuss the method in terms of the analysis of the method's characteristics and missed and false detections and the comparison of related works. Finally, the conclusion is given in Section 5.

2. Material and methods

2.1. EEG dataset

The EEG recordings used in this work come from the Epilepsy Center of the University Hospital of Freiburg, Germany. This database contains intracranial EEG signals of 21 patients. These EEG data were recorded by a Neurofile NT digital video-EEG system with 128 channels, a 256-Hz sampling rate, and a 16-bit analog-to-digital converter. Six channels of all implanted grid, strip, and depth electrodes were given for analyses, which were selected based on visual inspection of the raw data by certified epilepsy experts [37]. Three are focal channels, located near the epileptic focus, and three nonfocal channels. Only the three focal channels were chosen for seizure detection in this work. For each patient, there are 2–5 seizure events in the EEG recordings. The onset and end times of each seizure had been previously determined by experienced experts based on the identification of epileptic patterns preceding clinical manifestation of seizures in EEG recordings [38]. Additionally, each patient has approximate 24-hour interictal EEG recordings without seizure activity, i.e., nonseizure data. A detailed description of the database can be found in Ref. [39].

The task of this work was to propose a patient-specific seizure detection method. Hence, nonoverlapping training and testing datasets were created for each patient in the following way. For each of the patients, one or two seizures were chosen randomly. The EEG in these seizures and an equivalent amount of nonseizure EEG selected randomly from interictal recordings were used to construct the training dataset. Table 1 lists the detailed training dataset of 21 patients. All other available EEG data, which were not included in the training, could be used as testing data. In this work, we used 20-hour EEG data containing 1–4 seizure events to test the trained classifier for each patient. In total, 420 h of EEG data containing 59 seizure events were used for the performance assessment of the proposed seizure detection method.

2.2. Preprocessing

In the preprocessing stage, a 4th-order Chebyshev band-pass digital filter was first used in order to reduce the effect of artifacts. The cutoff frequency was empirically set to be 0.5 and 30 Hz. Then, the filtered multichannel EEG was segmented into 10-second epochs by a sliding window, without overlap between the adjacent epochs.

Table 1
Training dataset of 21 patients.

Patient	Number of seizure epochs	Number of nonseizure epochs	Total EEG epochs for training	Duration of training dataset (min)
1	6	6	12	2.0
2	16	16	32	5.3
3	15	15	30	5.0
4	12	12	24	4.0
5	3	3	6	1.0
6	7	7	14	2.3
7	10	10	20	3.3
8	20	20	40	6.7
9	40	40	80	13.3
10	189	189	378	63.0
11	7	7	14	2.3
12	8	8	16	2.7
13	26	26	52	8.7
14	68	68	136	22.7
15	5	5	10	1.7
16	22	22	44	7.3
17	11	11	22	3.7
18	7	7	14	2.3
19	4	4	8	1.3
20	20	20	40	6.7
21	9	9	18	3.0

2.3. Estimation of fractal dimension

According to the k-nearest neighbor algorithm for estimating fractal dimension [28,29], the average distance, $\langle r_k^\gamma \rangle$, of a point to its kth nearest neighbors is a function of k:

$$\langle r_k^\gamma \rangle = G(k,\gamma)k^{\gamma/D(\gamma)} \tag{1}$$

where $\gamma = (1\text{-}q)Dq$, $D(\gamma) = Dq$, and $G(k, \gamma)$ is a function of k and γ, which is near unity for large k. Here D_q is the q-order generalized dimensions. For $q = 0$, $\gamma = D_0$ and the fractal dimension is obtained. This means that the fractal dimension is the fixed point of the function $D(\gamma)$, and the fractal dimension of a segment of intracranial EEG signal can be estimated iteratively as follows.

Step 1. An initial value of γ, i.e., γ_0, is chosen arbitrarily. In this work, we chose $\gamma_0 = 1.5$.
Step 2. For each point of the EEG signal, the Euclidian distance r_{k_i} from its kth-nearest neighbor is calculated. Here, $k = k_{\min}, \ldots, k_{\max}$, $i = 1, 2, \ldots, N$, and N is the length of the EEG signal. In this study, $k_{\min}$ and $k_{\max}$ were selected as 1 and 100, respectively.
Step 3. For $j = 1, 2, \ldots$, the following recursive relations are applied:

$$D\left(\gamma_j\right) = \frac{\gamma_{j-1}}{s_{j-1}} \tag{2}$$

$$\gamma_j = D\left(\gamma_j\right) \tag{3}$$

where s_{j-1} is the slope of the best-fitting line at the points $\left(\ln(k),\ \ln\left\langle r_k^{\gamma_{j-1}}\right\rangle\right)$ and

$$\left\langle r_k^{\gamma_{j-1}}\right\rangle = \frac{1}{N}\sum_{i=1}^{N} r_{k_i}^{\gamma_{j-1}}, k = k_{\min}, \cdots k_{\max}. \tag{4}$$

The calculation is repeated until the maximum number of iterations is reached or the quantity $\left|\left(\gamma_j - \gamma_{j-1}\right)/\left[\frac{1}{2}\left(\gamma_j + \gamma_{j-1}\right)\right]\right|$ drops below a