Epilepsy & Behavior 52 (2015) 187–193

Contents lists available at ScienceDirect

Epilepsy & Behavior

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

Seizure detection approach using S-transform and singular value decomposition

Yudan Xia, Weidong Zhou *, Chengcheng Li, Qi Yuan, Shujuan Geng

School of Information Science and Engineering, Shandong University, Jinan 250100, China
Suzhou Institute of Shandong University, Suzhou 215123, China

ARTICLE INFO

Article history:
Received 17 April 2015
Revised 27 July 2015
Accepted 27 July 2015
Available online xxxx

Keywords:
S-transform
Singular value decomposition (SVD)
Seizure detection
Bayesian linear discriminant analysis (BLDA)

ABSTRACT

Automatic seizure detection plays a significant role in the diagnosis of epilepsy. This paper presents a novel method based on S-transform and singular value decomposition (SVD) for seizure detection. Primarily, S-transform is performed on EEG signals, and the obtained time–frequency matrix is divided into submatrices. Then, the singular values of each submatrix are extracted using singular value decomposition (SVD). Effective features are constructed by adding the largest singular values in the same frequency band together and fed into Bayesian linear discriminant analysis (BLDA) classifier for decision. Finally, postprocessing is applied to obtain higher sensitivity and lower false detection rate. A total of 183.07 hours of intracranial EEG recordings containing 82 seizure events from 20 patients were used to evaluate the system. The proposed method had a sensitivity of 96.40% and a specificity of 99.01%, with a false detection rate of 0.16/h.

1. Introduction

Epilepsy is a chronic neurological disorder characterized by paroxysmal and excessive neuronal discharges, which can result in loss of awareness or consciousness and disturbances of movement, sensation, mood, or mental function [1]. Approximately 1% of the world's population suffers from epilepsy [2,3]. Electroencephalography (EEG) is an important tool for the diagnosis of epilepsy, which reflects the electrical activity of the brain [4]. At present, long-term EEG recordings are usually inspected by experts visually to identify seizure activities, which is a time-consuming and tedious task. As a result, automatic seizure detection technology is very necessary to assist medical staff in analyzing EEG recordings.

In recent years, there have been various kinds of automatic seizure detection methods proposed. The method presented by Gotman [5] was widely applied, this technique decomposed EEG signals into half waves and detected seizures using peak amplitude, duration, slope, and sharpness. Later, Grewal and Gotman developed a seizure warning system utilizing spectral feature extraction and Bayes's theorem [6]. Nicolaou and Georgiou proposed a seizure detection algorithm based on permutation entropy (PE) and support vector machine (SVM) [7] to classify segments of normal and epileptiform EEGs. In addition, time–frequency analysis methods have also been employed for seizure detection [8–11], such as short-time Fourier transform (STFT) and wavelet transform (WT). Short-time Fourier transform decomposes EEG signals into time–frequency domain using a fixed and moving window function, but it has the limitation of analyzing signals at single resolution because of fixed window width. Wavelet transform solves the problem of STFT and provides multiresolution analysis via varying window width, which uses short windows at high frequencies and long windows at low frequencies. However, its accuracy depends on the chosen basis wavelet, and its computation is complicated.

The S-transform first introduced by Stockwell et al. [12] is an effective time–frequency analysis technique that has been widely used for signal processing, such as detection of multiple power quality disturbances [13], electrocardiogram (ECG) beat classification [14], and heart sound segmentation [15]. Stockwell transform is a combination of continuous wavelet transform (CWT) and STFT and overcomes the disadvantages of them [16]. It presents a good time–frequency resolution characteristic by using a moving and scalable localizing Gaussian window. Singular value decomposition (SVD) is a data decomposition approach that describes the distribution of matrix data and can reduce the effect of noise. Using SVD, Kim et al. extracted illumination–invariant features for face recognition [17]. Kanjilal et al. employed SVD on the composite maternal ECG signal for fetal ECG extraction [18]. Singular value decomposition was also utilized for earthquake prediction [19]. The singular values are very stable and robust to the change of matrix elements. In this study, we used the singular values of EEG time–frequency matrix obtained with S-transform as features for seizure detection.

Many of classifiers have been used for seizure detection, such as support vector machine (SVM), extreme learning machine (ELM), and artificial neural network (ANN). Bayesian linear discriminant analysis (BLDA) can be treated as an extension of Fisher's linear discriminant

* Corresponding author at: School of Information Science and Engineering, Shandong University, 27 Shanda Road, Jinan 250100, China. Tel.: +86 531 88361551.
E-mail address: wdzhou@sdu.edu.cn (W. Zhou).

http://dx.doi.org/10.1016/j.yebeh.2015.07.043
1525-5050/

analysis (FLDA) [20], which is an efficient method for machine learning. In contrast to FLDA, BLDA employs regularization to avoid overfitting to high dimensional and noisy datasets and has shown its superior performance for motor imagery classification [21]. Bayesian linear discriminant analysis was employed to train the classifier in this study.

In this paper, we first propose a novel method for seizure detection using S-transform in combination with SVD. The rest of this paper is organized as follows. Section 2 introduces the material and methods including six parts: (1) a brief introduction of the intracranial EEG (iEEG) dataset, (2) the S-transform time–frequency analysis, (3) the feature extraction method based on SVD, (4) the Bayesian linear discriminant analysis, (5) postprocessing, and (6) the performance evaluation approach. Section 3 shows the experimental results, and is followed by a discussion of the proposed method in Section 4. Finally, the conclusion is brought forward in Section 5.

2. Material and methods

2.1. EEG dataset

The EEG data used in this study were acquired from the Epilepsy Center of the University Hospital of Freiburg, Germany [22]. The database contains intracranial EEG recordings of 21 patients suffering from medically intractable focal epilepsy. All EEGs were recorded using 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 the EEG recordings were available for each patient, including three focal channels (i.e., near the epileptic focus) and three extrafocal channels. Seizure onset and offset times were notated by the experts based on EEG recordings.

In this study, only three focal channels of the EEGs from 20 patients were chosen for seizure detection. The EEG data from patient 10 were discarded because of electrode box disconnection and reconnection. For each patient, there were 2- to 5-h of EEG data containing seizure events. A total of 183.07-h of intracranial EEG recordings containing 82 seizure events were used in this work. The details of the used EEG data for each patient are summarized in Table 1.

The long-term EEG recordings were analyzed using a 4-s sliding window without overlap between epochs. Each epoch contained 1024 points. For each patient, one seizure event or two seizure events and the same number of nonseizure epochs were chosen randomly as training dataset, and all the remaining EEG data were utilized as testing data. In total, 156.91-h of EEG data (1.32-h of seizure data and 155.59-h of nonseizure data) containing 55 seizure events from 20 patients were selected as test data.

Table 1
Details of the database used in this study. The acronyms used in the table are SP: simple partial seizure, CP: complex partial seizure, and GTC: generalized tonic–clonic seizure.

Patient	Seizure type	Seizure origin	EEG length (h)	Number of used seizures	Total number of EEG epochs for training
1	SP	Frontal	9	4	8
2	SP, CP, GTC	Temporal	5.62	3	52
3	SP, CP	Frontal	8.19	5	14
4	SP, CP, GTC	Temporal	10	5	18
5	SP, CP, GTC	Frontal	9.90	5	56
6	CP, GTC	Temporal/occipital	6.42	3	40
7	SP, CP, GTC	Temporal	6	3	18
8	SP, CP	Frontal	3.57	2	54
9	CP, GTC	Temporal/occipital	10	5	44
11	SP, CP, GTC	Parietal	8	4	68
12	SP, CP, GTC	Temporal	8	4	16
13	SP, CP, GTC	Temporal/occipital	4	2	38
14	CP, GTC	Frontal/temporal	7	4	58
15	SP, CP, GTC	Temporal	10	4	74
16	SP, CP, GTC	Temporal	11.69	5	64
17	SP, CP, GTC	Temporal	14.80	5	28
18	SP, CP	Frontal	12.97	5	26
19	SP, CP, GTC	Frontal	13	4	14
20	SP, CP, GTC	Temporal/parietal	12.91	5	36
21	SP, CP	Temporal	12	5	94
Total	–	–	183.07	82	820

2.2. S-transform time–frequency analysis

Stockwell transform, which is the development of CWT and STFT, is a new technique for the analysis of nonstationary signals [12]. Stockwell transform not only realizes a progressive multiresolution analysis but also has a low computation complexity. The S-transform of signal $x(t)$ is defined by

$$S(\tau, f) = e^{j2\pi f\tau} W(\tau, f) \tag{1}$$

$$W(\tau, d) = \int_{-\infty}^{+\infty} x(t)\omega(t-\tau, d)dt \tag{2}$$

where $W(\tau,f)$ is the CWT of $x(t)$, $\omega(t,f)$ is mother wavelet function that is defined by

$$\omega(t, f) = \frac{|f|}{\sqrt{2\pi}} e^{-\frac{t^2 f^2}{2}} e^{-j2\pi f t} \tag{3}$$

and the frequency f decides the width of wavelet basis. In addition, the mother wavelet function has to satisfy the condition of zero mean.

The S-transform of signal $x(t)$ is finally given as follows:

$$S(\tau, f) = \int_{-\infty}^{+\infty} x(t) \frac{|f|}{\sqrt{2\pi}} e^{-\frac{(\tau-t)^2 f^2}{2}} e^{-i2\pi f t} dt. \tag{4}$$

The application of S-transform decomposes a given dataset into a complex time–frequency matrix whose rows correspond to frequency and columns to time. The matrix contains much important information such as amplitude, phase, and frequency. In this study, we make use of the amplitude matrix for feature extraction. Seizures in recorded EEG usually occur below 30 Hz [23]; thus, the frequency range of S-transform is selected from 1 to 30 Hz. With S-transform, each epoch of data yields a 30×1024 amplitude matrix, in which 30 represents frequency sampling points from 1 Hz to 30 Hz and 1024 represents time sampling points. In order to analyze the local characteristic and to reduce the dimension of the matrix, we divide the matrix into 12 blocks. The time axis is divided into 3 segments averagely, while the frequency axis is divided into 4 segments according to different frequency band distributions, including delta (1–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), and beta (12–30 Hz). As a result, 12 submatrices are generated for subsequent processing.

2.3. SVD-based feature extraction

Singular value decomposition could decompose a matrix into three matrices. According to the SVD theory, for a given matrix $\mathbf{A}_{m \times n} \in \mathbf{R}^{m \times n}$, there exist two orthogonal matrices $\mathbf{U}_{m \times m} \in \mathbf{R}^{m \times m}$ and $\mathbf{V}_{n \times n} \in \mathbf{R}^{n \times n}$ which satisfy the following equation:

$$\mathbf{A} = \mathbf{U}\mathbf{\Lambda}\mathbf{V}^{\mathrm{T}} \tag{5}$$

where Λ is an $m \times n$ diagonal matrix, whose diagonal elements are the singular values of matrix $\mathbf{A}_{m \times n}$ that are sorted in a decreasing way such that $\sigma_1 \geq \sigma_2 \ldots \geq \sigma_n \geq 0$. The columns of the orthogonal matrices $\mathbf{U}_{m \times m}$ and $\mathbf{V}_{n \times n}$ are called the left and right singular vectors of matrix $\mathbf{A}_{m \times n}$, respectively.