Biomedical Signal Processing and Control 10 (2014) 1–10

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

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

A framework on wavelet-based nonlinear features and extreme learning machine for epileptic seizure detection

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ARTICLE INFO

Article history:
Received 16 August 2013
Received in revised form 22 October 2013
Accepted 29 November 2013
Available online 22 December 2013

Keywords:
Seizure detection
Wavelet decomposition
Approximate entropy (ApEn)
Sample entropy (SampEn)
Recurrence quantification analysis (RQA)
Extreme learning machine (ELM)
Support vector machine (SVM)

ABSTRACT

Background: Many investigations based on nonlinear methods have been carried out for the research of seizure detection. However, some of these nonlinear measures cannot achieve satisfying performance without considering the basic rhythms of epileptic EEGs.
New method: To overcome the defects, this paper proposed a framework on wavelet-based nonlinear features and extreme learning machine (ELM) for the seizure detection. Three nonlinear methods, i.e., approximate entropy (ApEn), sample entropy (SampEn) and recurrence quantification analysis (RQA) were computed from orignal EEG signals and corresponding wavelet decomposed sub-bands separately. The wavelet-based energy was measured as the comparative. Then the combination of sub-band features was fed to ELM and SVM classifier respectively.
Results: The decomposed sub-band signals show significant discrimination between interictal and ictal states and the union of sub-band features helps to achieve better detection. All the three nonlinear methods show higher sensitivity than the wavelet-based energy analysis using the proposed framework. The wavelet-based SampEn-ELM detector reaches the best performance with a sensitivity of 92.6% and a false detection rate (FDR) of 0.078. Compared with SVM, the ELM detector is better in terms of detection accuracy and learning efficiency.
Comparison with existing method(s): The decomposition of original signals into sub-bands leads to better identification of seizure events compared with that of the existing nonlinear methods without considering the time–frequency decomposition.
Conclusions: The proposed framework achieves not only a high detection accuracy but also a very fast learning speed, which makes it feasible for the further development of the automatic seizure detection system.

1. Introduction

Epilepsy is a serious disorder of the central nervous system, which is characterized by recurrent seizures that occur at unpredictable occasions. Approximately 1% of the general population exhibits symptoms of epilepsy [1]. Frequent seizures increase the risk of sustaining physical injuries and may even result in death [2,3].

The electroencephalography signals (EEGs) have been viewed as the practical way for epilepsy monitoring and diagnosis. However, the visual inspection of long time EEG data is very laborious work for medical doctors [4] and the detection of the seizure activities is a challenging job even for the trained neurologist since EEG signals are easy to be contaminated by the excessive presence of artifacts. Hence, it is significant to develop the automatic system to liberate the neurologists from long-term EEG interpretation.

Many methods have been explored for the automatic analysis of epileptic EEGs and those studies mainly focus on feature extraction of epileptic characteristics and classification of seizure activities. Some of the efficient seizure detection methods are based on power spectral analysis [5–7], wavelet decomposition [1,8] and morphologic pattern [9]. Some of these studies have been tested on commercial software such as IdentEventTM [7]. In the recent years, nonlinear analysis techniques have gained more popularity with promising results due to the nonlinear and dynamic nature of EEG signals [10–13]. The summary of such studies is given in the discussion part of the paper. In this study, we assess and compare three nonlinear feature extraction techniques: approximate entropy (ApEn) [14–16], sample entropy (SampEn) [17–19] and recurrence quantification analysis (RQA) [20–25].

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http://dx.doi.org/10.1016/j.bspc.2013.11.010

Table 1
Information of patients and EEG data.

Patient	Sex	Age	Analyzed channel	Number of seizures	Average seizure duration (s)	Total interictal period (h)
1	F	11	T8-P8	7	63.1	39
2	M	11	T8-P8	3	57.3	33
3	F	14	T7-P7	7	53.1	31
4	M	22	T7-P7	4	85.5	98.5
5	F	7	F7-T7	5	111.6	34
6	M	3.5	T7-P7	5	183.8	15
7	F	10	P8-O2	4	69	65
8	M	3	T7-P7	6	63.7	65
9	F	12	F7-T7	3	268.7	31
10	F	6	T7-P7	8	36.75	23
11	F	9	T7-P7	3	68	31
12	–	–	T7-P7	13	27.7	10
Mean	–	9.9	–	5.7	90.7	39.6
Std	–	5.3	–	2.9	69.2	24.9

The information of Patient No. 12 is not currently declared by the provider.

Recent investigations indicate in some cases, EEG wavelet sub-bands may yield more accurate information about constituent neuronal activities underlying EEG signals [8]. The characteristics which are not evident in the original full-spectrum EEG may be distinct in separate sub-band signals. In our experiments, some of the nonlinear measures cannot gain satisfying classification performance based on the analysis of original EEG signals. Hence, our proposed method includes the time–frequency decomposition to extract the data characteristics by different resolutions of time and frequency scales. In addition, a wavelet-based energy analysis is carried out for the comparison with nonlinear methods.

In the research of epileptic seizure detection, classification method is another focus of this type of work. Up to now, the design of detectors still encounters big challenge because the long time recording generates extremely large amount of data and has considerable overlap of seizure and non-seizure states [3,26]. To improve the overall performance of a detection system, the designers must confront a steep tradeoff between detector sensitivity and specificity and make a compromise between detector efficiency and specificity. The first widely applicable technique was developed on wavelet filter to extract the frequency features and constructed a neural network detector for classification [5]. Back-propagation (BP) algorithm and support vector machine (SVM) [3] have been widely explored as the detector for classification. However, when the sample size is large, the learning speed of both methods is too slow to meet the requirements for real-time applications. A novel learning algorithm extreme learning machine (ELM) can not only avoid falling into local optima but also largely improve the learning speed [19,27]. In this research, the wavelet-based nonlinear features were fed to the ELM classifier for detecting epileptic seizures with overall consideration of detector sensitivity, specificity and efficiency. The goal of this research is to develop a highly sensitive automatic system with a low false detection rate to assist neurologists to review potential EEG epochs containing seizures.

2. Materials and methods

2.1. Dataset

The data set explored in this study consists of 476 h continuous EEG sampled at 256 Hz. The data set was recorded from 12 pediatric patients at Children's Hospital Boston. Subjects were monitored for up to several days following withdrawal of anti-seizure medication in order to characterize their seizures and assess their candidacy for surgical intervention. In all these records, 68 events were judged as clinical seizures by medical doctors. The beginning and end of each seizure was annotated by the experts. The data was segmented into 1 h long records. The international 10-20 system of EEG electrode positions and nomenclature was used for these recordings. Most records contain 23 channels of EEG signals (24 or 26 in a few cases). More details of the EEG data used in this paper are described in Shoeb and Guttag [3]. The data is available in the CHB-MIT database, which can be downloaded from the PhysioNet website: http://www.physionet.org/physiobank/database/chbmit/. Seizure is not always present in all EEG channels [26] and knowledge of seizure onset channels is necessary. For this purpose, a 25-s file with each seizure activity on one of the seizure onset channels is created from the above dataset. The channel selection is based on the knowledge of the epileptic focus. Further details regarding the patients and EEG dataset can be found in Table 1. This event-based data is then used for training the classifier which is explained in Section 2.5. The file length of seizure activities should be chosen with caution. A small length focuses on seizure onset, but also causes the detector to fail to detect a seizure whenever the onset changes. A large length enables the detection of later seizure stages, but increases the detector's false detection rate because it will extend the decision boundary to enclose more non-seizure vectors [3]. In this research, we set file length to 25 s.

2.2. System overview

The block diagram of the detection system is shown in Fig. 1. First, original EEG signals are decomposed into sub-band signals. Then three nonlinear features, i.e., approximate entropy (ApEn), sample entropy (SampEn), recurrence quantification analysis (RQA) and a comparative, i.e., wavelet-based energy are computed from the original EEG signals and the corresponding decomposed sub-band signals separately. Further, the union of the sub-band features is fed to an efficient classifier – extreme learning machine (ELM) to determine the class membership of these feature vectors: 1 – seizure, 0 – non-seizure. Finally, the performance of ELM is compared with another detector – support vector machine (SVM) in terms of sensitivity, false detection rate and consuming time.

2.3. Wavelet decomposition

Since the sampling frequency of the EEG is 256 Hz, the maximum available frequency is half of the sampling frequency, i.e.,

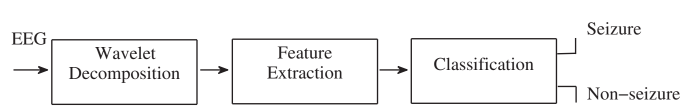

Fig. 1. Block diagram of the detection system.