Biomedical Signal Processing and Control 34 (2017) 114–125

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

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

Automatic epileptic EEG detection using DT-CWT-based non-linear features

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ARTICLE INFO

Article history:
Received 4 October 2016
Received in revised form
20 December 2016
Accepted 21 January 2017
Available online 1 February 2017

Keywords:
Epilepsy
EEG
DT-CWT
Non-linear features

ABSTRACT

The epilepsy is a type of common neurological disorder plaguing many people around the world. A novel method based on the dual-tree complex wavelet transform (DT-CWT), in this study, is proposed to develop a reliable diagnosis method for the epileptic EEG detection. We explore the ability of DT-CWT to decompose the original EEG into five constituent sub-bands, which are associated with non-linear features such as the Hurst exponent (H), Fractal Dimension (FD) and Permutation Entropy (PE). Furthermore, influences of different filter types on the DT-CWT are considered in this study as well. With these features, the support vector machine (SVM) configured with filters of the near-symmetric 13/19 tap filters (NS 13/19) and Q-shift 14/14 tap filters (QS 14/14) is found to achieve the preferable classification accuracy of 98.87%, which is visibly higher than that with discrete wavelet transform (DWT)-based features. Results demonstrate that the technique proposed by us can not only provide significant performance with less computational cost but also can implement simply. It will be a potential method for practical applications extended to the development of a real-time brain monitoring system.

1. Introduction

As the second most common serious neurological disorder in human beings followed by stroke, the epilepsy is a chronic condition of the nervous system, and is characterized by recurrent unprovoked seizures [1]. Based on a report of the World Health Organization (WHO), more than 50 million people globally have epilepsy, of which 80% live in low- and middle-income countries [2]. Persons who have epilepsy, besides, not only bear illness but also suffer from the stigma and discrimination. For epilepsy detection, a conventional method is to check the electroencephalogram (EEG) visually by expert neurologists, which is time-consuming and error-prone. Therefore, it is necessary to develop a reliable and automatic way to help epilepsy patient cope with the disease.

EEG signals indicate the electrical activity of the brain, which contain the useful information about the brain state to study brain functions and neurological disorders [3]. Due to the complex interconnections among billions of neurons, EEG signals are complex, non-linear, non-stationary and random in nature [4], which indeed brings great difficulties for the seizure detection. The common used methods, currently, could be summarized as the time domain analysis [5], frequency domain analysis [6], time-frequency domain analysis [7] and non-linear dynamics analysis [4,8]. As regard to characteristics of EEG, the time-frequency domain and non-linear dynamics analysis are widely brought into play among the existing literatures. Ocak [9], Guo et al. [10], Adeli et al. [11] and Kumar et al. [12] detected epilepsy with the use of discrete wavelet transform (DWT) along with non-linear features. Acharya et al. [13] proposed a novel automatic technique based on the wavelet packet decomposition (WPD). Non-linear parameters such as the Fractal Dimension (FD) [14], the largest Lyapunov exponent (LLE) [15,16], Hurst exponent (H) [17] and Entropies [4], are likely to be utilized to characterize such signals. Results of the above studies indicate that there is still the space of improvement for the classification accuracy.

As some studies have proved that the features derived from sub-bands are more significant than those from original signals [11]. Because of the alternately sampling, however, the traditional wavelet transform is easy to bring in unreal frequency component, which would lead to the halfway band separation. This disadvantage would reduce the describing ability for features. Hence, a new approach based on the dual-tree complex wavelet transform (DT-CWT) has been adopted in this paper. The DT-CWT is a kind of wavelet transform improved that is widely used in fields of the image de-noising [18] and fault detection [19]. Dos et al. [20–22] and Chen et al. [23] had demonstrated the idea of using fea-

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http://dx.doi.org/10.1016/j.bspc.2017.01.010

tures obtained from DT-CWT coefficients for EEG signal recognition. Nevertheless, these works are mainly focused on the combination of DT-CWT decomposition and time or time-frequency domain features. More importantly, few researches had reported on the analysis of various filters. The objective of this paper is to explore the potential of DT-CWT in epilepsy diagnosis while developing a method that can make a good balance between classification efficiency and accuracy. The brain is a kind of highly complex non-linear system, and the chaotic phenomenon is found in it. Hereby, non-linear analysis methods can reveal the maximum information from EEG signals, which could lead to dependable analysis of results. And the EEG rhythms can better reflect the real physiology activities in brain. Therefore, deep and elaborate researches on DT-CWT and non-linear features have been done in this paper.

Different from aforementioned literatures, our study is based on the ability of DT-CWT reconstruction. Besides making the necessary analysis to proposed scheme, some contributions have been made in this paper. First, numerous experiments are conducted with consideration of the effects caused by different filters. Second, we have investigated the performance of using various non-linear features obtained from DT-CWT components. Third, the performance of the method is compared with the DWT model on the aspect of both accuracy and robustness. Moreover, four commonly used wavelet basis are taken into account. Finally, in order to make rigorous conclusions, Wilcoxon test is carried out to assess the significant difference between different approaches. All these analysis are not presented in other similar works.

The proposed method in this study is described in Fig. 1. Firstly, signals are pre-processed by a low-pass filter at 60 Hz. Secondly, the DT-CWT is adopted to decompose signals into sub-bands of delta (0–4 Hz), theta (4–8 Hz), alpha (8–15 Hz), beta (15–30 Hz) and gamma (30–60 Hz). Finally, non-linear features such as FD, H and Permutation Entropy (PE) are acquired from different constituent sub-bands and fed to four classifiers for the epilepsy detection, namely Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree (DT) and Random Forest (RF). Results indicate that, in aspects of the classification accuracy (98.87%) and computing time (122.65 ms), the present method can be used to design an accurate classification system for epilepsy diagnosis.

2. Data

The EEG data used in this paper is the publicly available database from University of Bonn, Germany [24]. Five sub-sets are contained in database denoted as A, B, C, D, and E, while each containing 100 single-channel EEG signal of 23.6 s duration. All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. The data were digitized at 173.61 samples per second using 12 bit A/D resolution. The case of A, D and E is a classical classification problem which is conforming to actual needs, and some researches have been conducted specifically for this problem [16,25–27]. Sub-sets A, D, E are thus used for further analysis in this study, and the description of considering sets are summarized in Table 1. Exemplary EEG signals are depicted in Fig. 2.

3. Methods

3.1. Dual-tree complex wavelet transform (DT-CWT)

Introduced by Kingsbury [28], the DT-CWT can generate complex coefficients by using a dual tree of wavelet filters to obtain the real and imaginary parts. Compared with the DWT, advancing properties of DT-CWT are approximate shift invariance and preferable anti-aliasing [29]. The factor that RF is more beneficial for classification can be attributed to the structure of 'two parallel trees' (as illustrated in Fig. 4, Trees A and B represent real and imaginary parts of the transform respectively).

Fig. 3 describes how these two trees are sampled during the signal processing. Points sampled by the Tree A are in the red color; while those by Tree B are in blue. As shown in Fig. 3, the sampling location of Tree B is always maintained under a neutral position in that of Tree A, by which the missing information of Tree A can be exactly collected by Tree B. That is, the delay between these two trees is a sampling value interval, which is equal to process signals without alternately sampling. Such two trees, therefore, can complement and fulfill each other. Moreover, effects of alternately sampling would be weakened; the problem of frequency aliasing would be restrained. Also reconstruction components are closer to real results.

Fig. 4 shows the process of decomposition and reconstruction for a 3-level DT-CWT. During the decomposition, the h0 and h1 represent for the low- and high-pass filter pair for Tree A; while the g1 and g0 denote that for Tree B. Similarly, during the reconstruction, the h0′ and h1′ are the filter pair for Tree A, and the g1′ and g0′are that for Tree B. Moreover, (↓2) is the down-sampling operator; while (↑2) is the up-sampling one [30,31]. We, in this paper, use the DT-CWT toolbox written by Kingsbury. Two filters should be set for the transform: one is for level 1 and the other is for the level ≥2. Filters of level 1 can be set as the Antonini 9/7 tap filters (An 9/7), the LeGall 5/3 tap filters (LG 5/3), the near-symmetric 5/7 tap filters (NS 5/7) or the near-symmetric 13/19 tap filters (NS 13/19). Moreover, there are four options for filters of the level ≥2, including the Q-shift 10/10 tap filters (QS 10/10), the Q-shift 14/14 tap filters (QS 14/14), the Q-shift 16/16 tap filters (QS 16/16) or the Q-shift 18/18 tap filters (QS 18/18). The choice of appropriate filters holds great significance impact on the quality of results with regard to the classifiers. In this regard, the analysis of different filters are considered in this paper, which will be concretely described in the Section 4.

3.2. Non-linear features

In this contribution, three non-linear features are employed to characterize the signals. A brief introduction is made in this part.

3.2.1. Hurst exponent

The Hurst exponent (H) is a statistical parameter that is used to measure the correlation of points in a time series. It is defined as the relative tendency of a time series to either regress to a longer term mean value or 'cluster' in a direction. As the H can classify time series based on their predictability and chaos levels, it may be a useful tool in identifying deviations from the normal patterns of brain activity during interruptions of seizures [32]. The generalized equation of H is presented as follows:

$$H = \frac{\log\left(R/S\right)}{\log\left(T\right)} \tag{1}$$

Where R is the difference between the maximum and minimum deviation from the mean, and S represents the standard deviation. T is the duration of the sample data.

3.2.2. Fractal dimension

Fractal Dimension (FD) can be seen as a powerful tool for complexity measurement of biological signals. It can give an indication of how completely the fractal appears to fill space [25,33]. In this work, Higuchi method is utilized to calculate FD, which appeared to be more accurate in estimating this indicator. Given a finite set