Accurate classification of epilepsy seizure types using wavelet packet decomposition and local detrended fluctuation analysis

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Electroencephalogram (EEG) signals are widely used in diagnosis of epilepsy. Accurate classification of seizure types based on EEG signals can provide vital information for diagnosis and treatment. Since visual inspection and interpretation of seizure types are time consuming and prone to errors, a novel classification method combining wavelet packet decomposition (WPD) and local detrended fluctuation analysis (L-DFA) is proposed for the computer-aided diagnostic system. The proposed method is able to classify a wide variety of seizures automatically and accurately. As the first step towards this goal, raw EEG signals are decomposed by WPD according to intrinsic frequency bands of human brain. Then L-DFA is applied to characterise the dynamical fractal structure of sub-band signals. Finally, EEG signals are classified by support vector machine based on the combined fractal spectrum features. The experimental results on Temple University Hospital database show that the proposed method achieves a total classification accuracy of 97.80%, outperforming existing methods based on the same database.

Introduction: Epilepsy is one of the most common and devastating neurological diseases in worldwide, characterised by spontaneously recurrent seizures. Seizure types vary across patients with different epileptic aetiologies and focuses. Therefore, accurate classification of seizure types is required to provide important information for epilepsy diagnosis and reliable guidance in treatment.

Several computer-aided diagnostic (CAD) systems have been proposed to automatically detect seizures and seizure types based on electroencephalogram (EEG). In [1], frequency-domain features were extracted by short-time Fourier transforms and stacked as the input of the convolutional neural network. In [2], time-domain statistical features were utilised for classification including mean, variance, skewness, kurtosis, standard deviation and interquartile range. In [3], the seizure type detection was based on the combination features of Mel-frequency cepstral coefficients and Hjorth descriptor. Since EEG is a kind of highly non-stationary and complex bioelectrical signal, the above-mentioned features are not sufficient enough to reveal the characteristics of different types of seizure processes. Thus, this Letter proposes a new classification method, focusing on the feature extraction process that is well adaptive to non-stationary EEG signals.

The proposed method is based on the combining use of wavelet packet decomposition (WPD) and local detrended fluctuation analysis (L-DFA). WPD is a powerful tool to analyse non-stationary signals and is used to decompose raw EEG into sub-band signals in this work. In WPD, a complete binary tree is created by decomposing both detail coefficients and approximation coefficients of the previous level without omission or redundancy. Thus, WPD can provide a multi-scale signal set with higher frequency resolution, compared with discrete wavelet transform. The detail information in each sub-band is well preserved for subsequent fractal analysis by L-DFA. Conventional fractal analysis estimates the Hurst exponent that defines the particular kind of scale invariant structure of the time series. As an extension of detrended fluctuation analysis (DFA), L-DFA was conceived by Ihlen [4] to describe the dynamical fractal structure of biomedical signals. The fractal spectrum is calculated from the local Hurst exponent which will fluctuate in time and identify the time instant of structural changes within the signal. Spatial and temporal variations in the structure of EEG can be effectively characterised by L-DFA. Key parameters are extracted from the fractal spectrum in each sub-band and a high-dimensional feature vector is formed for the sample session. Different types of seizures are classified via support vector machine (SVM) based on the precisely designed features.

Database: The proposed method is implemented on version 1.5.0 of the Temple University Hospital Seizure Corpus (TUSZ) [5] which was recorded from 637 patients according to 10–20 International system electrode placement. The database consists of simple partial seizure (SPSZ), complex partial seizure (CPSZ), focal non-specific seizure (FNSZ), generalised non-specific seizure (GNSZ), absence seizure (ABSZ), tonic seizure (TNSZ), tonic-clonic seizure (TCSZ) and non-seizure sessions (NORM). These data were annotated carefully by a neurologist and divided into training set (2370 seizure sessions, 3730 non-seizure sessions) and test set (685 seizure sessions, 727 non-seizure sessions) in advance.

Wavelet packet decomposition: For n-level decomposition, WPD produces 2^n different sets of coefficients that give the time-frequency representation of the original signal. In this work, a seven-level WPD is implemented on raw EEG signals with Daubechies 4 (db4) wavelet. According to the commonly used intrinsic frequency bands in human brain researches, the wavelet packet coefficients are combined to reconstruct the signals in six sub-bands that are delta (0–3 Hz), theta (4–7 Hz), alpha (8–13 Hz), beta (14–30 Hz), gamma-1 (31–60 Hz) and gamma-2 (61–120 Hz) band.

Local detrended fluctuation analysis: For a given time series $\{x_i\}$ with length N, the scale-dependent measure μ_{s,t_0} is defined [4] as a root-mean square fluctuation of the integrated response time series y_t around a polynomial trend $\hat{y}_{t,m}$ of order m within a floating trial interval $[t_0-s/2,\ t_0+s/2]$, where t_0 is the centre of the interval and s is the sample size (i.e. scale)

$$y_t = \sum_{i=1}^{t} (x_i - \overline{x}) \tag{1}$$

$$\mu_{s,t_0} = \sqrt{\frac{1}{s} \sum_{t=t_0-s/2}^{t_0+s/2} (y_t - \hat{y}_{t,m})^2} \tag{2}$$

A second-order polynomial detrending (i.e. $m=2$) of the response time series is used in this work. The local Hurst exponent h_t is estimated as the linear regression slope of log-log plot of μ_{s,t_0} versus scale s, which portrays the local variation and self-similarity of the time series $\{x_i\}$. Fig. 1 gives the $\{h_t\}$ series in six sub-bands for channel FP1-F7 of a NORM segment and a SPSZ segment, respectively. The mode of $\{h_t\}$, which indicates the maximum distribution probability, is marked by a red dashed line.

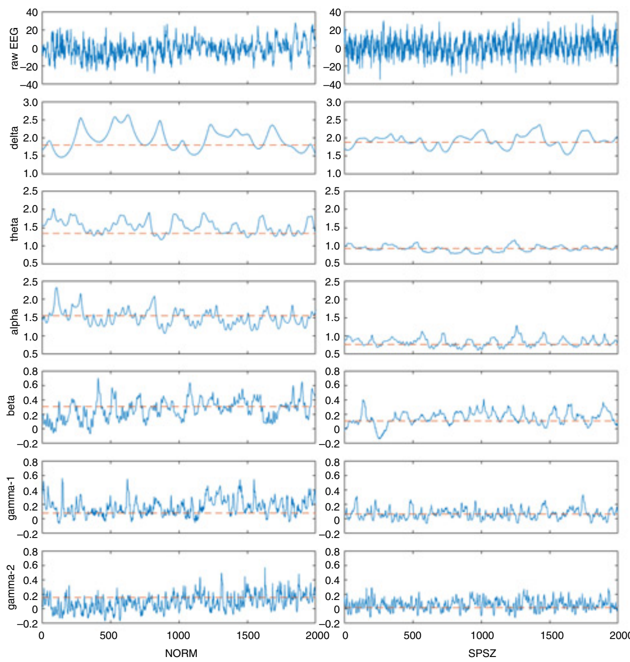

Fig. 1 *Local Hurst exponent series in six sub-bands for channel FP1-F7 of the NORM segment and SPSZ segment*

Feature extraction: As shown in Fig. 1, there are distinguishable differences between the $\{h_t\}$ series of the NORM and SPSZ segment, including extremums, modes and fluctuation patterns. The fractal spectrum D_h [4] was calculated based on the normalised distribution of local Hurst exponent, by which dynamical fractal properties of EEG segments can be effectively reflected. As an example, the spectrums of multi-channel signals in beta band are given in Fig. 2, corresponding to one NORM segment and seven different kinds of seizure segments, respectively.

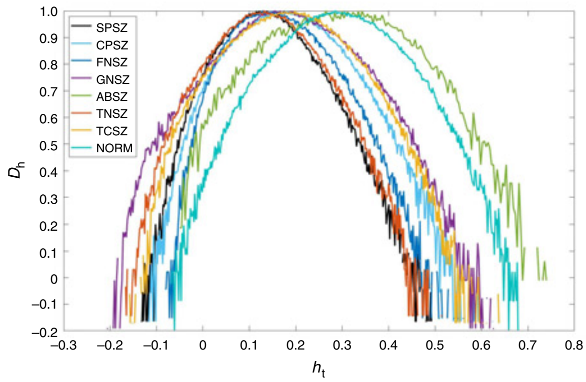

Fig. 2 *Fractal spectrums of the NORM segment and seven different kinds of seizure segments in beta band*

A three-dimensional (3D) feature vector is formed by prominent spectrum indexes that are the minimum abscissa value ($f1$), the maximum abscissa value ($f3$) and the abscissa value of apex ($f2$). The beta-band feature vectors of 1412 samples in the test set were mapped to a 3D space, as shown in Fig. 3. It is demonstrated that the fractal spectrum-based feature has good discrimination ability for normal processes and different kinds of seizure processes. Finally, the 3D features of six sub-bands are formed to 18-dimensional vectors for classification.

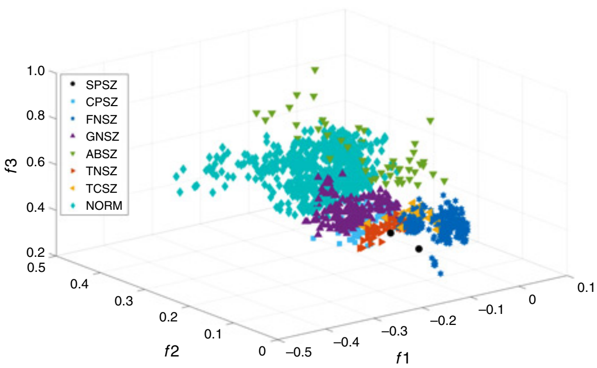

Fig. 3 *Spectrum-based feature vectors (beta-band) of 1412 samples in 3D space*

Experimental results: The classification is conducted by a SVM classifier with the radial basis function kernel. The training set and test set were set up in advance by Temple University Hospital (TUH) with more details given in [5]. In order to overcome the class imbalance challenge of the dataset, we have used a resampling technique to generate balanced samples in the training phase. Thus, the practicality and reliability of the classifier can be ensured. Table 1 gives the classification performance of the proposed method on the test set, evaluated in terms of sensitivity (SEN), specificity (SPE) and accuracy (ACC). Performance comparison with related works is provided by Table 2. Our work achieves the highest total accuracy for the 8-class (including non-seizure sessions) seizure classification problem.

Table 1: Classification performance of proposed method

	SPSZ	CPSZ	FNSZ	GNSZ	ABSZ	TNSZ	TCSZ	NORM
SEN, %	100	95.24	100	97.18	100	92	100	97.94
SPE, %	99.14	99.77	99.82	99.68	99.78	99.85	99.85	100
ACC, %	99.15	99.50	99.15	99.36	99.79	99.58	99.86	98.94

Table 2: Comparison between proposed method and related studies

Method	Database	Types	Total accuracy, %
Ragha *et al.* [1]	TUSZ	8 (7 seizure types)	84.06
Wijayanto *et al.* [2]	TUSZ	5 (4 seizure types)	95
Saputro *et al.* [3]	TUSZ	4 (3 seizure types)	91.4
proposed method	TUSZ	8 (7 seizure types)	97.80

Conclusion: In this Letter, we present a novel method to detect seizures and identify seizure types for the CAD system of epilepsy. The proposed method can effectively characterise the structure variations of non-stationary EEG by the combining use of WPD and L-DFA. The structure characteristics are revealed by the sub-band local fractal spectrums. The integrated feature based on local fractal spectrums shows good discrimination ability for normal processes and different kinds of seizure processes. The classification performance is evaluated on the TUSZ test set with seven types of seizures. The proposed method achieves a total accuracy of 97.80%, outperforming related works on the same database. In future studies, we will furtherly improve the classification ability for some specific seizure types.

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One or more of the Figures in this Letter are available in colour online.

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