Classification of single-channel EEG signals for epileptic seizures detection based on hybrid features

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Abstract.
BACKGROUND: Epilepsy is a common chronic neurological disorder of the brain. Clinically, epileptic seizures are usually detected via the continuous monitoring of electroencephalogram (EEG) signals by experienced neurophysiologists.
OBJECTIVE: In order to detect epileptic seizures automatically with a satisfactory precision, a new method is proposed which defines hybrid features that could characterize the epileptiform waves and classify single-channel EEG signals.
METHODS: The hybrid features consist of both the ones usually used in EEG signal analysis and the Kraskov entropy based on Hilbert-Huang Transform which is proposed for the first time. With the hybrid features, EEG signals are classified and the epileptic seizures are detected.
RESULTS: Three datasets are used for test on three binary-classification problems defined by clinical requirements for epileptic seizures detection. Experimental results show that the accuracy, sensitivity and specificity of the proposed methods outperform two state-of-the-art methods, especially on the databases containing signals from different sources.
CONCLUSIONS: The proposed method provides a new avenue to assist neurophysiologists in diagnosing epileptic seizures automatically and accurately.

Keywords: Epilepsy, epileptic seizures detection, electroencephalogram (EEG), hybrid features, Kraskov entropy, Hilbert-Huang transform

1. Introduction

Epilepsy is one of the leading neurological diseases in the world and it is triggered by the recurrent electrical discharge of the neurons of cerebral cortex [1]. The electroencephalogram (EEG) signal is usually utilized by neurophysiologists to diagnose epileptic seizures as a gold standard. Electroencephalogram activity resembling spikes, sharp waves and polyspike complexes is named epileptiform waves [2]. Clinically, the detection of epileptic seizures can be obtained by the visual scanning of EEG signals by experienced neurophysiologists who make their elementary diagnosis via observing the frequency of epileptiform discharges in the EEG signals. However, there are many inevitable negative factors that

influence the diagnosis precision. For example, the individual characteristics of patients such as gender, age and sleep qualities could have an influence on EEG signals. In fact, the epilepsy is patient-specific. Machine learning algorithms have been used recently to help characterize the representative features of epilepsy and detect the epileptic seizures automatically. In the learning process, feature extraction is a crucial step which has a key effect on the classification performance.

In the recent past, much research has been proposed to extract features such as wavelet features, entropy and fractal dimension for epileptic seizures detection. Vidyaratne extracted two features, the energy feature of specific sub-bands decomposed by the harmonic wavelet packet transform and the fractal dimension, and used the Relevance Vector Machine to classify epileptic seizure and seizure-free EEG signals [3]. The accuracy of 99.8%, sensitivity of 99% and specificity of 100% were obtained on the Bonn dataset, and the sensitivity of 96% was obtained on CHB-MIT Scalp EEG database. Similarly, the fractal dimension of decomposed sub-bands using the analytic time-frequency flexible wavelet transform was used with the sensitivity of 100% for epileptic seizures detection [4]. Samiee classified the EEG signals for epileptic seizure detection by the width of the largest local Gabor binary patterns by using the sparse rational decomposition as a feature [5]. The accuracy of 85.41%, specificity of 99.09% and sensitivity of 70.39% were achieved on CHB-MIT Scalp EEG database. Jaiswal proposed two features, namely the Local Neighbor Description Model and One-Dimensional Gradient Model with several classifiers to achieve the classification [6]. It achieved the average classification accuracy above 99.82% on the Bonn dataset. Chen proposed a method using features which are the Fourier coefficients of non-subsampled wavelet transformation and the Nearest Neighbor classifier [7]. It achieved the 100% accuracy on Bonn dataset. Patidar introduced a new feature with the Kraskov entropy of a set of band-limited signals decomposed by the Tunable-Q Wavelet Transform [8]. The accuracy, sensitivity and specificity were more than 97% on Bonn dataset. Another method by Bajaj extracted features of the instantaneous areas based on the Hilbert-Huang transform and used a threshold method to classify [9]. Using the dataset from the Epilepsy Center of the University Hospital of Freiburg, the accuracy, sensitivity and specificity were 97.75%, 90% and 89.31% respectively.

The existing methods mentioned above have been effective in the classification of epileptic seizure and seizure-free periods on specific databases. However, the performance may be unsatisfactory when the methods are used on different databases, due to the complexity of EEG signals and their feature diversity across databases. In this paper, a new feature that could represent the epileptic-related EEG signals is designed which integrates the Hilbert-Huang Transform (HHT) and Kraskov entropy. With hybrid features including this one, a novel method is proposed to detect epileptic seizures automatically. It is observed that the feature combination plays an important role in improving the classification performance. The classification results show that the proposed method using the hybrid feature has better performance in classifying seizure and seizure-free EEG signals for the automatic diagnosis of epilepsy than previous methods on the database containing signals from different sources.

2. Methodology

2.1. Data

Previous methods often used a specific database to verify the performance of epileptic seizures detection. In fact, using independent datasets would be better in verifying the generality and universality of methods. In this study, three EEG databases were used, denoted as Data A, Data B, and Data C respectively.

Data A was developed by Bonn University, which includes five subsets denoted as Z, O, F, N and S [10]. There were 100 segmented single-channel EEG signals in each subset, with a sampling rate of 173.61 Hz and the duration of 23.6 seconds. Subsets Z and O contained the EEG recordings of five healthy volunteers whose eyes were opened and closed respectively. Subsets F and N contained the EEG signals recorded from epileptic patients before epileptic attack at epileptogenic zones. Subsets S consisted of EEG signals recorded from patients under the seizure attack. All the five subsets have been used in this research and regrouped to three classes according to our classification problems in later description.

Data B was collected from the CHB-MIT Scalp EEG database publicly available at PhysioNet, which consisted of 23 pediatric subjects with intractable seizures from Children's Hospital in Boston [11]. The sampling rate of EEG signals in this database was 256 Hz, and the length of each EEG recording was several hours. In this research, each signal was divided into segments with the length of 23.6 seconds.

Many previous research results have shown that the machine learning algorithms may sometimes over-fit the data space when using a unique database. To verify the generalization of algorithms, the data from different sources with various parameters or characteristics are usually combined together. Accordingly, to mimic the complexity of clinical applications, we built the Data C, which was a combined EEG database including part of the data from the two databases. Signals in Data A were resampled at 256 Hz for consistency. Additionally, all signals in Data A were normalized, and a band-pass filter with the frequency range from 0.35 Hz to 45 Hz was used to alleviate the influence of noise.

To detect the epileptic seizures using the EEG signals, three types of signals were defined according to previous research. Electroencephalogram (EEG) segments labeled as 'Normal' constituted EEG records from five healthy volunteers (Z and O) in Data A and normal EEG records in Data B. Electroencephalogram (EEG) segments labeled as 'Interictal' consisted of EEG records from five patients with epilepsy before epileptic attack in Data A (F and N) and EEG records which were before the periods of epileptic seizures in Data B. Electroencephalogram segments labeled as 'Ictal' composed EEG records from epileptic patients during epileptic attack in both Data A and Data B. Specially, the EEG signals labeled as 'Non-Ictal' included the two classes of 'Normal' and 'Interictal'.

2.2. Classification problems

Considering the clinical requirements for detecting and predicting epileptic seizures, and further revealing the mechanism of epilepsy, three types of binary-classification problems for EEG signals in different status are usually studied. They are defined as follows.

CP-1: Classification for {Normal} and {Ictal};

There are differences that are reflected in EEG signals between healthy people and epileptic patients. The work of classification could help to diagnose the epileptic seizures and explore the pathogenesis of epilepsy.

CP-2: Classification for {Interictal} and {Ictal};

This classification was performed on the subjects with epilepsy. It could help to detect the onset time and notify doctors to rescue patients, which may provide the alert as soon as possible.

CP-3: Classification for {Non-Ictal} and {Ictal}.

The classification aims at improving the diagnosis accuracy. In clinical, EEG signals of healthy people are similar to those belonging to the class {Interictal} of epileptic patients. This method enables the observers to distinguish the two classes {Non-ictal} and {Ictal} and increases the diagnosis precision of epilepsy.

2.3. Feature extraction

In this paper, three types of features are integrated to classify single-channel EEG signals for epileptic seizure detection. Firstly, the novel proposed type of feature is the Kraskov entropy based on the Hilbert-Huang Transform (HHT). Additionally, the other two types of features are the instantaneous area of analytic intrinsic mode functions of EEG signals and the Kraskov entropy applied on tunable-Q wavelet transform respectively [8,9].

2.3.1. The proposed feature extraction method

The novelly proposed feature is the Kraskov entropy based on the Hilbert-Huang Transform (HHT). The following sections are the details of the processing for the feature extraction and classification steps.

Hilbert-Huang Transform is a common method for analyzing the time-frequency distribution of signals before feature extraction [12]. It has more appropriate inherent properties than conventional wavelet transform in dealing with unstable signals. Concretely, there are two steps to implement this transformation. Firstly, the Empirical Mode Decomposition (EMD) is used to decompose EEG signals into several levels of Intrinsic Modal Functions (IMF). Secondly, the Hilbert Transform (HT) is performed on each IMF to produce a group of analytical signals.

Empirical Mode Decomposition is a screening process decomposing signals into some limited IMFs. It is usually an indispensable preprocessing for Hilbert-Huang Transform (HT) because it decomposes the original signals into the ones that satisfy the prerequisites for performing HT, i.e. 1) the difference between the number of extreme values and the number of zero crossings of each IMF is less than two; and 2) the upper and lower envelopes of each IMF are locally symmetric on the time axis. The basic principle of EMD is decomposing original signals with multi-frequency components into some IMFs with a single frequency and a residual signal. Primarily, we denote the original signal as $s(t)$:

$$s(t) = \sum_{i=1}^{M} IMF_i(t) + r_M(t) \tag{1}$$

where M is number of IMFs and $IMF_i(t)$ represents the ith IMF, and the last residue is expressed by $r_M(t)$.

The processes of EMD are as below:

1) Locate all points of local extreme values for $s(t)$;
2) Implement cubic spline analysis on the above points of local extreme values to fit the upper and lower envelopes respectively;
3) Calculate the mean value $m(t)$ of the upper and lower envelopes;
4) Obtain a mode function $x(t) = s(t) - m(t)$;
5) In the ith step, analyze $x_i(t)$ to see whether it meets the two prerequisites for performing HT. If satisfied, then let $IMF_i(t)$ equal to $x_i(t)$ and compute the new residue $r_M(t) = s(t) - x_i(t)$. Sequentially, we decompose $r_M(t)$ in the same way until the residual signal is a monotonic function or below the threshold. If the obtained residual signal isn't satisfied, steps 1) to 4) have to be repeated circularly.

Briefly, the inherent attribute of the Hilbert transform is regarded as an ideal 90 degree phase shifter. The HT for each IMF can be represented as

$$H[IMF_i(t)] = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{IMF_i(\tau)}{t - \tau} d\tau \tag{2}$$

The spectrum of a real signal is conjugate symmetric. However, only the positive spectrum is authentically necessary for this analysis. In order to remove the redundancy in spectrum, the formation of an analytical signal is a common way as

$$z(t) = IMF_i(t) + jH[IMF_i(t)] = A_i(t)\exp(j\varphi(t)) \tag{3}$$

where the imaginary component of the analytical signal $z(t)$ is the Hilbert Transform of $IMF_i(t)$. $A_i(t)$ and $\varphi_i(t)$ are the amplitude and the phase of $IMF_i(t)$ respectively.

$$A_i(t) = \sqrt{[IMF_i(t)]^2 + \{H[IMF_i(t)]\}^2} \tag{4}$$

$$\varphi_i(t) = \arctan\left(\frac{H[IMF_i(t)]}{IMF_i(t)}\right) \tag{5}$$

In this work, the amplitude $A_i(t)$ of each $IMF_i(t)$ is computed as the next original signal. Firstly, it removes some subtle noise hiding in signals and gains intrinsic mode signals with high-quality. Secondly, it acquires desynchronization features reflecting the changeable energy distribution of EEG signals.

Kraskov entropy was presented by Kraskov in 2004 [13]. It had been used to improve estimators for mutual information between two different classes of random samples. In this study, we utilized the Kraskov entropy as a non-linear feature for epileptic seizures detection. Considering pathological mechanism of epilepsy, the abrupt changes of EEG signals caused by the sudden abnormal discharges of brain neurons are hard to predict. Nevertheless, the Kraskov entropy is sensitive and capable of manifesting this abrupt transform. Regarding to statistical theories, the Kraskov entropy can quantitatively show the epileptic temporal changes and reduce variance of the estimator.

The traditional Shannon entropy $H(x)$ is defined as

$$H(x) = -\int u(x)\log(u(x))dx \tag{6}$$

where $u(x)$ is a probability density function. The Kraskov entropy is the unbiased estimator of Shannon entropy. For a random time series sample $X = (x_1, x_2, \ldots, x_N)$, it can be formulated as

$$\hat{H}(X) = -\frac{1}{N}\sum_{i=1}^{N}\log(\hat{u}(x_i)) \tag{7}$$

where $\log\hat{u}(x_i)$ is an unbiased estimator of unknown $\log(u(x_i))$. In order to calculate the value of $\log(u(x_i))$, the resulting k-nearest neighbor estimate was utilized. $\log(u(x_i))$ is formulated as

$$\log(u(x_i)) \approx \varphi(k) - \varphi(N) - \ldots - dE(\log\epsilon) - \log(V_d) \tag{8}$$

where $\epsilon(i)$ equals to twice the distance from x_i to its kth neighbor, $\varphi(x)$ is the digamma function, d is the dimension of the random sample X, and V_d represents the volume of the d-dimensional unit ball, where one has $V_d = \pi^{d/2}/\Gamma(1+d/2)/2^d$ for the Euclidean norm. Finally, the Kraskov entropy is represented as $\hat{H}(X)$,

$$\hat{H}(X) = -\varphi(k) + \varphi(N) + \log(V_d) + \ldots \frac{d}{N}\sum_{i=1}^{N}\log(2\delta(x_i, k)) \tag{9}$$

where $\delta(x_i, k)$ is the distance from x_i to its kth neighbor.

In this research, we proposed a new feature extraction method, i.e. calculating the Kraskov Entropy of the signals decomposed by Hilbert-Huang Transform. The aim of the EMD method is to decompose

the nonlinear and non-stationary EEG signals into a finite set of amplitude and frequency modulated oscillating components, i.e. IMFs, where each IMF represents narrow-band symmetric waveforms with different frequencies ranking from high to low. In order to retain the main energy information of EEG signals and remove the redundancy, envelopes of IMFs are obtained by the Hilbert Transform. Then the Kraskov entropy of each envelope is computed as the first type of features for epileptic seizure detection.

2.3.2. The Kraskov entropy based on tunable-Q wavelet transform

Similar to the type of features used by Patidar, the Kraskov entropy of some sub-band signals decomposed by tunable-Q wavelet transform is also used as the second type of features in this work [8]. Tunable-Q Wavelet Transform (TQWT) is a proficient transform for the analysis of oscillatory signals such as EEG, where a J-level decomposition can be achieved by attaching two band filter banks to the previous low-pass sub-band signals. Each filter bank consists of a pair of high-pass and low-pass filters. The parameters r and Q are introduced to represent the total over-sampling rate and the frequency-to-bandwidth ratio of the high-pass sub-band signal, which is the last sub-band after the desirable decomposition.

In this study, the original EEG signals were firstly decomposed into limited sub-bands using a level J decomposition of TQWT. The Kraskov entropy was then performed on part of the sub-bands, after which calculation the final outcome is set as the second type of features.

2.3.3. The instantaneous area of IMFs using Hilbert-Huang transform

Similarly, the third type of feature comes from the idea of Bajaj, which is the instantaneous area of each IMF obtained from HHT [9]. As the aforementioned context, finite IMFs with different frequency ranges were obtained from HHT. To better detect the epileptic seizures in EEG signals, an overlapping window with a fixed size was slid on each IMF. The size L of the window was set as 3840, which corresponds to 15 seconds, i.e. the smallest duration of a temporal epileptic seizure. The window overlap was set as 2560 to optimize the detection of epileptic seizures in this work. The instantaneous area of each IMF was computed as

$$S_{IMF_m}(n) = \pi \sum_{i=n}^{L-1+n} r(i)^2 \tag{10}$$

where $S_{IMFm}(n)$ is the instantaneous area of the mth IMF, n represents time instant, i.e. the first point after moving the window, $r(i)$ is the distance from the ith sample point to the center of the circle in the complex plane for the mth IMF.

2.3.4. Feature combination

After the feature extraction, the three types of features were combined to form the final hybrid feature vector. At the beginning, the original signals were fully decomposed into 10 or 11 IMFs. Further tests have shown that the first three IMFs could characterize the EEG signals best and are most appropriate for epileptic seizure detection. Accordingly, the first type of feature is three-dimensional. For the second type of feature, the same method was utilized to choose the combination of sub-band signals as the proposed. It has been demonstrated that the first three sub-bands are more useful to classify the EEG signals. We adopted the method and chose the best value 1 of Q when the performance reached the best values. In order to verify the effectiveness of decomposing signals and ensure the integrity of the information, it was necessary to reconstruct the signal using the decomposed sub-bands. High values of r were usually accompanied with the approximate reconstruction of the original signal [14]. On the

Table 1
Performance evaluation of three classification problems on Data A

	Methods	ACC (%)	SEN (%)	SPC (%)
CP-1	Chen et al. [7]	99.00	97.00	100.00
	Patidar and Panigrahi [8]	99.33	98.00	100.00
	Proposed method	99.00	98.00	99.50
CP-2	Chen et al. [7]	98.33	95.00	100.00
	Patidar and Panigrahi [8]	96.33	95.00	97.00
	Proposed method	97.00	97.00	97.00
CP-3	Chen et al. [7]	99.20	96.00	100.00
	Patidar and Panigrahi [8]	97.60	93.00	98.75
	Proposed method	98.20	96.00	98.75

Table 2
Performance evaluation of three classification problems on Data B

	Methods	ACC (%)	SEN (%)	SPC (%)
CP-1	Chen et al. [7]	69.09	65.92	72.46
	Patidar and Panigrahi [8]	66.30	67.06	65.59
	Proposed method	69.69	74.00	64.96
CP-2	Chen et al. [7]	64.97	64.01	66.03
	Patidar and Panigrahi [8]	73.07	71.21	74.96
	Proposed method	72.10	74.78	69.34
CP-3	Chen et al. [7]	71.36	52.06	81.10
	Patidar and Panigrahi [8]	75.21	50.96	87.37
	Proposed method	73.80	57.46	81.96

basis of previous experience, we chose 3 as the most appropriate value of r. As a result, the second type of feature was also three-dimensional. Similarly, for the third type of feature, the first three IMFs were chosen. Due to the usage of the moving window, the third type of feature was six-dimensional. Combining the three types of features, a hybrid feature vector with twelve dimensions was put into the classifier to classify the different classes of EEG signals for epileptic seizure detection.

2.4. LS-SVM classifier

To realize the classification, the LS-SVM classifier was used. It is a least squares version of Support Vector Machine. The input space was mapped to a so-called high dimensional feature space, where an optimal linear regression hyperplane will be located eventually. It has been validated contribute to a good performance in various classification problems for either biomedical signals or images [15,16]. In this paper, the LS-SVM with the radial basis function kernel was trained to classify the EEG signals.

3. Results and discussion

In this work, three classification problems were tested on three databases, which focus on different EEG signal discrimination tasks, i.e. 'Normal' versus 'Ictal', 'Interictal' versus 'Ictal', and 'Non-Ictal' versus 'Ictal' respectively. The 10-fold cross-validation was used to verify the performance. Three common statistical parameters were computed to evaluate the generality and universality of the proposed model for the clinical application, including accuracy (ACC), sensitivity (SEN) and specificity (SPC). The performance was also compared to the two latest methods by Chen and Patidar [7,8]. In previous

Table 3
Performance evaluation of three classification problems on Data C

	Methods	ACC (%)	SEN (%)	SPC (%)
CP-1	Chen et al. [7]	60.38	56.24	63.44
	Patidar and Panigrahi [8]	68.72	60.73	74.59
	Proposed method	77.72	72.25	81.70
CP-2	Chen et al. [7]	62.60	45.26	75.18
	Patidar and Panigrahi [8]	68.28	59.52	74.65
	Proposed method	82.82	74.93	88.56
CP-3	Chen et al. [7]	69.00	37.15	80.64
	Patidar and Panigrahi [8]	72.70	25.87	89.77
	Proposed method	85.30	59.93	94.55

works, these two methods were only tested on Data A. In our research, they were also tested on Data B and Data C respectively. Experimental results on three datasets are shown in Tables 1–3 respectively.

Table 1 shows the performance on Data A. As described in Section 2.1, the EEG signals from this database were elaborately selected from typical EEG signals with high signal-to-noise ratio and distinguishable features. This database is used by many researchers as a basic verification dataset. It can be observed that all three methods can achieve good performance for the three classification problems.

To further verify the feasibility and universality of our method, the other two Data B and Data C were exploited. Tables 2 and 3 show the performance evaluation on Data B and Data C respectively. As shown in Table 2, the performance of the proposed method was comparable with the other two methods. For most parameters, the performance of the proposed method was similar to or better than the other two methods.

More importantly, as shown in Table 3, the proposed method had the better performance than the other two in all tasks and all parameters. For classifying 'Normal' and 'Ictal' EEG signals, the accuracy was 77.72%, the sensitivity was 72.25%, and the specificity was 81.70%. For classifying 'Interictal' and 'Ictal' EEG signals, the accuracy was 82.82%, the sensitivity was 74.93% and specificity was 88.56%. For the third task of classifying 'Non-Ictal' and 'Ictal' EEG signals, the accuracy, sensitivity, and specificity were 85.30%, 59.93%, and 94.55% respectively. Data C was built with data from different sources, which is more similar to the real situation of practical applications. Accordingly, the good performance of the proposed method on that database showed that the proposed hybrid features have better feasibility and universality for epileptic seizure detection.

As shown in Table 1, all the methods showed the good performance in three classification problems. That was because of the standardization and high signal-to-noise ratio of signals in Data A. All the methods could capture the characteristics of EEG signals, and they were all able to solve the three classification problems with ideal performance.

The results in Table 2 showed that the sensitivities of the proposed work were highest, which means the proposed method is helpful to decrease the misdiagnosis rates. Moreover, there were obvious differences between the results in Tables 1 and 2 because of the diversity of databases. It was noted that the properties of the parameters characterizing the databases played a role on epileptic classification problems. As a result, the classification performance on Data C was especially important. As shown in Table 3, the proposed method was more applicable to the databases that possess various components. It had the potential to deal with the signals from complex and various situations in practical applications.

The computation cost was also compared between the proposed method and the other two. The proposed method costs similar time to Paditar's method, but several times more than Chen's method. It is still not fast enough to meet the requirement of real-time epileptic seizure diagnosis. Furthermore, to

validate its generalization, clinical data from different sources are necessary. Both the combination of features and the selection of classifiers could be further optimized with more available data.

4. Conclusions

In this paper, a novel method to classify three classes of EEG signals for epileptic seizure detection was proposed. A new feature extraction method was also proposed for the first time, which calculates the Kraskov entropy of the envelopes of IMF signals decomposed by Hilbert-Huang Transform. Integrating this type of feature with other two types of features, the hybrid twelve-dimensional feature vector was input into the LS-SVM classifier for classification. To evaluate the generality and universality of the proposed method, three different datasets were used, and three binary-classification problems were defined. Experimental results have validated the good performance of the proposed method and the hybrid features in detecting epileptic seizures. Although there are still some problems for real-time applications, the proposed method provides a new avenue to assist neurophysiologists in diagnosing epileptic seizures automatically and accurately.

Acknowledgments

Conflict of interest

None to report.

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