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Technical Note

Hilbert marginal spectrum analysis for automatic seizure detection in EEG signals

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ABSTRACT

In this paper, we present a new technique for automatic seizure detection in electroencephalogram (EEG) signals by using Hilbert marginal spectrum (HMS) analysis. As the EEG signal is highly nonlinear and nonstationary, the traditional Fourier analysis which expands signals in terms of sinusoids cannot appropriately represent the amplitude contribution from each frequency value. The HMS is derived from the empirical mode decomposition (EMD) which decomposes signal into a collection of intrinsic mode functions (IMFs). Since this decomposition is based on the local characteristic time scale of the signal, it can be well applied to nonlinear and nonstationary processes. In this work, the spectral entropies and energy features of frequency-bands of the rhythms using HMS analysis are extracted and fed into the support vector machine (SVM) for seizure detection of EEG signals. A final comparison between the results obtained with the developed technique and results adopted by Polat and coworkers using Fourier analysis with the same database is given to show the effectiveness of this technique for seizure detection.

1. Introduction

Epileptic seizure is a group of brain disorder characterized predominantly by recurrent and unpredictable interruptions of normal brain function. Epilepsy is one of the most common neurological disorders, 0.6–0.8% of the world's population suffers [1]. Electroencephalogram (EEG) is a valuable measure of the brain's electrical function and generated by the cerebral cortex's nerve cells, it has been a valuable clinical tool for epilepsy evaluation and treatment. Generally, a continuous recording of the EEG lasts as long as one week for epilepsy detection. Since the seizures are episodic in their occurrences, detection of epileptic seizure by visual inspection of EEG signal is very time consuming and maybe inaccurate. For this reason, automatic detection of EEG signals is highly useful and required for the diagnosis of this disease.

Recently, many signal analyzing and processing techniques have been proposed for studying EEG signals [2–10]. Among these methods, traditional Fourier spectral analysis has been used to extract features of EEG signals for detection of seizure [2,3]. However, the EEG is a highly nonstationary process, and the Fourier analysis which expands signals in terms of sinusoids cannot appropriately represent the amplitude contribution from each frequency value. To address this problem, several joint time-frequency analysis based methods have been proposed and applied for detection of epileptic seizure from EEG signals [4–8]. The short time Fourier transform extracts several frames of the signal to be analyzed with a window that moves with time and was used to calculate the power spectrum density of each segment of EEG signals [4]. The wavelet transform is similar to the windowed Fourier transform and the values of approximate entropy derived from the wavelet coefficients were used to characterize the predictability of the EEG data [5,6]. The Wigner-Ville distribution and its improved version, smoothed pseudo Wigner-Ville distribution (SPWVD) have received considerable attention in recent years as an analysis tool for nonstationary signals [7,8], and sub-band frequencies of the sub-band signals of SPWVD based time-frequency spectrum have been used as features for detection of seizure [7].

Above mentioned time-frequency analysis methods have their own advantage in nonstationary signal processing indeed, but they are all based on Fourier theory and have not given a new definition of frequency mathematically. Hilbert–Huang transform (HHT) makes creative improvement of frequency definition for the first time, which is proposed by Huang et al. in 1998 [11]. This new signal analyzing method does not handle the signal processing problems from the view that the basic component of signal is sinusoid, instead of signals called intrinsic mode functions (IMFs). The

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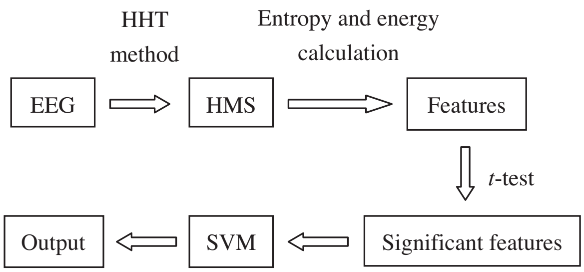

Fig. 1. Block diagram of the proposed method.

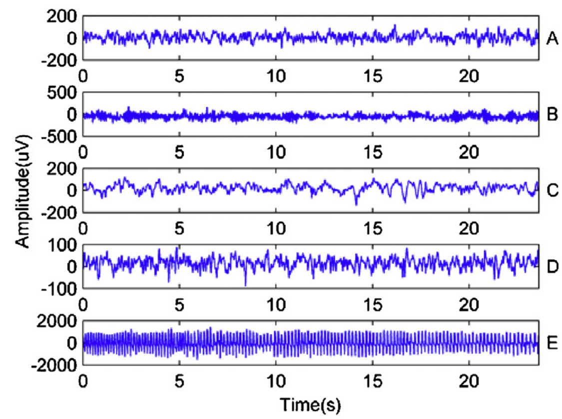

Fig. 2. Exemplary EEG segments from each of the five subsets (A, B, C, D, and E).

IMF is generated by empirical mode decomposition (EMD) method which is intuitive, direct, and adaptive for signal decomposing. The EMD method has been successfully applied in signal analyzing and processing [12–22]. The IMF can be both stationary and nonstationary, while the sinusoid is the very special situation of IMF. Hence, HHT has well solved the contradiction of imperfectness of nonstationary signals processed by Fourier transform and established the foundation in analyzing signals of time-varying frequency and amplitude.

Hilbert marginal spectrum (HMS) analysis is based on HHT, and possesses the advantage of HHT. Recently, the method of HMS combined with k-Means was used and acquired good performance in epileptic seizure detection [23]. In this paper, we present a new method for automatic detection of seizure in EEG signals by using HMS analysis. Fig. 1 illustrates the block diagram of the proposed method. We propose spectral entropy and energy features corresponding to the frequency-bands of the rhythms in EEG signals for seizure detection. A hypothesis testing is conducted for feature selection. The features with lower p-values are used and fed into support vector machine (SVM) with radial basis function (RBF) for classification of seizure and nonseizure EEG signals. We also make a comparison with the method of traditional Fourier spectrum analysis. The experimental results show that the HMS analysis based method provides better classification than the Fourier spectrum analysis method conducted in this paper and also in Polat's research [3].

The rest of the paper is organized as follows: a description of the EEG dataset used in this work, the HHT and its marginal spectrum analysis method, comparison with Fourier spectrum, feature extraction and SVM classifier are presented in Section 2. The experimental results and discussion are given in Section 3. Finally, Section 4 concludes the paper.

2. Materials and methods

2.1. Dataset

The EEG data used in this work are taken from a public accessible signals database [24]. The dataset is composed by five subsets (denoted as A, B, C, D and E) and consists of 100 signals of EEGs with 4097 samples for each one of the signals. Each of these signals lasts 23.6 s with a sampling frequency of 173.61 Hz. Datasets A and B consisted of segments acquired from surface EEG recordings of five healthy volunteers with eyes open and closed. Samples in dataset C and D were recorded from the hippocampal formation of the opposite hemisphere and epileptogenic zone of the brain, respectively. Sets C and D contained activity measured during seizure free intervals from epileptic patients. The subset E only contains seizure activity. Typical EEG signals are shown in Fig. 2.

2.2. The Hilbert–Huang transform and its marginal spectrum

The HHT consists of two components: EMD and Hilbert spectral analysis [11]. As the key part of HHT, the method of EMD to decompose signal is intuitive, direct and adaptive. This decomposition method is based on local characteristic of local time domain of data. Based on this characteristic, any nonlinear and nonstationary signal can be decomposed into a set of IMFs which are amplitude and frequency modulated signals.

The definition of IMF is proposed mainly to get the physical meaning of the instantaneous frequency. Each IMF should satisfy two basic conditions [11]: (1) The number of extreme points and the number of zero crossings must be either equal or differ at most by one; (2) At any time point, the local mean value of the envelope which defined by the average of the maximum and minimum envelopes is zero. The first condition is similar to the narrow-band requirement for a stationary Gaussian process. The second condition modifies a global requirement to a local one, and is necessary to ensure that the instantaneous frequency will not have unwanted fluctuations as induced by asymmetric waveforms [11]. The intrinsic mode functions are obtained by using the EMD decomposition algorithm and denoted $c_i(t)$. At the end of the algorithm, the original signal $x(t)$ can be represented as:

$$x(t)=\sum_{i=1}^{n}c_i(t)+r_n(t) \tag{1}$$

where n is the number of intrinsic modes, $c_i(t)$ is the ith IMF, and $r_n(t)$ is the final residual which can be interpreted as the DC component of the signal.

For any real IMF $c(t)$, its Hilbert transform $c_H(t)$ is defined as:

$$c_H(t)=\frac{1}{\pi}P\int_{-\infty}^{+\infty}\frac{c(\tau)}{t-\tau}d\tau \tag{2}$$

where P is the Cauchy principal value of the singular integral. Then the analytic signal of the $c(t)$ can be defined as below:

$$z(t)=c(t)+jc_H(t)=a(t)e^{j\phi(t)} \tag{3}$$

The amplitude of pre-envelope $a(t)$ and instantaneous phase $\phi(t)$ are defined as:

$$a(t)=\sqrt{c(t)^2+c_H(t)^2} \tag{4}$$

$$\phi(t)=\arctan\frac{c_H(t)}{c(t)} \tag{5}$$

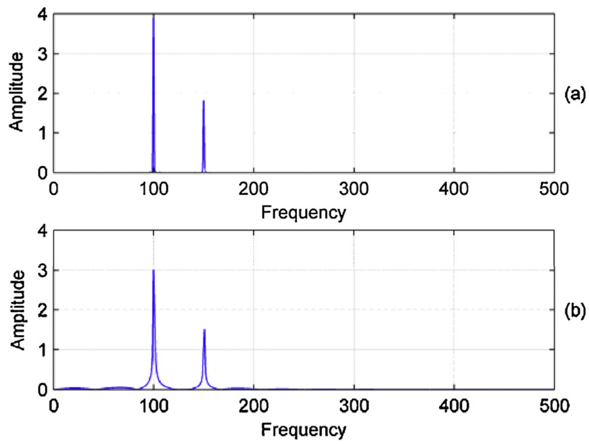

Fig. 3. HMS (a) and Fourier spectrum (b) of a finite-duration sinusoidal signal with the same frequency resolution.

The instantaneous frequency can then be written as the time derivative of the phase, as shown below:

$$w(t) = \frac{d\phi(t)}{dt} \tag{6}$$

Thus the original signal can be expressed in the following form:

$$X(t) = \mathrm{Re}\sum_{i=1}^{n} a_i(t)\ \exp\left(j\int w_i(t)dt\right) \tag{7}$$

It enables us to represent the amplitude and the instantaneous frequency as functions of time in a three-dimensional plot. This frequency-time distribution of the amplitude is designated as the Hilbert–Huang spectrum, $H(w, t)$.

Last, with the Hilbert–Huang spectrum defined, the marginal spectrum $h(w)$, would then be defined as:

$$h(w) = \int_0^T H(w, t)dt \tag{8}$$

The marginal spectrum offers a measure of total amplitude (or energy) contribution from each frequency value [11].

2.3. Comparison with Fourier spectrum

In most cases, the HMS in energy is very similar to Fourier in case the data from stationary and linear process. However, as pointed out by Huang et al. [11], the frequency in either $H(w, t)$ or $h(w)$ has a totally different meaning from the Fourier spectral analysis. The same data if expanded in Fourier representation can be expressed as:

$$X(t) = \sum_{i=1}^{\infty} a_i e^{(iw_i t)} \tag{9}$$

where a_i and w_i are constants. Compared with Eq. (7), it is clear that the IMF obtained by EMD method represents a generalized Fourier expansion. In the Fourier representation, the existence of energy at a frequency means a component of a sine or a cosine wave persisted through the time span of the data, while the HMS describes the probability that a frequency exists at some local time point in the signal [11].

Considering the case of the sum of two sine waves with 1 kHz sample rate as

$$x(t) = 4\sin(2\pi \times 100t) + 2\sin(2\pi \times 150t), \quad t \in [0, 1] \tag{10}$$

Fig. 3(a) and (b) shows the HMS and Fourier spectrum of above finite-duration sinusoidal signal with the same frequency resolution. It can be clearly observed from Fig. 3(a) that the two spectral lines of HMS are clearly separated, which means that it has the higher resolution ratio. For the Fourier spectrum in Fig. 3(b), each spectral line has more than one, which means there exists severe energy leakage and the resolution ratio is lower. Besides, the height of the spectral line represents the possibility of the relative frequency existence, the higher the spectral line is, the greater possibility the relative frequency exists [11]. Hence, compared with Fourier spectrum, the HMS can reflect the frequency components of signals more accurately.

2.4. Feature extraction

To verify the effectiveness of the proposed method, extracting adequate features from EEG signals is important and required. In this paper, the entropy and energy features of the HMS are extracted and discussed.

2.4.1. Spectral entropies

Entropy is the measure of disorder in physical systems and related with the amount of information that may be gained by observations of disordered systems. It is a convenient way of quantifying the distribution of spectral power. Data with a broad, flat probability distribution will have high entropy, while data with a narrow, peaked, distribution will have low entropy [26]. The Fourier spectrum based entropies have been studied and successfully applied in many fields [25,26]. As applied to EEG, entropy is the statistical descriptor of the variability within the EEG signal. As mentioned in above sections, HMS has excellent property in nonstationary signal processing, so the HMS based entropy may provide a good performance in EEG signal classification. In this work, the spectral entropy of Shannon, Renyi and Tsallis are discussed.

In order to calculate the entropy, the spectrum should be converted into a probability mass function by normalizing the spectrum firstly. Eq. (11) is used for normalization.

$$p_i = \frac{P_i}{\sum_{i=1}^{n} P_i} \tag{11}$$

where P_i is the energy of the ith frequency component of the spectrum and p_i is the probability mass function of the spectrum.

Then, the Shannon entropy can be written as [27]:

$$SEN = -\sum_{i=1}^{n} p_i\ \log p_i \tag{12}$$

where p_i is the probability of occurrence of an event, here it refers the probability density of the spectrum and $\sum_{i=1}^{n} p_i = 1$.

The Renyi entropy is defined as [28]:

$$REN_\alpha = \frac{1}{1-\alpha}\log\sum_{i=1}^{n} p_i^\alpha \tag{13}$$

where the additional parameter α is used to make it more or less sensitive to the shape of probability distributions.

Another generalized entropy which is defined by Constantino Tsallis [29], is given by

$$TEN_\alpha = \frac{1}{\alpha-1}\left(1-\sum_{i=1}^{n} p_i^\alpha\right) \tag{14}$$

Renyi and Tsallis entropies reduce to the Shannon entropy in case of $\alpha = 1$. In this work, the parameter α of Renyi and Tsallis entropy are both set to 2.

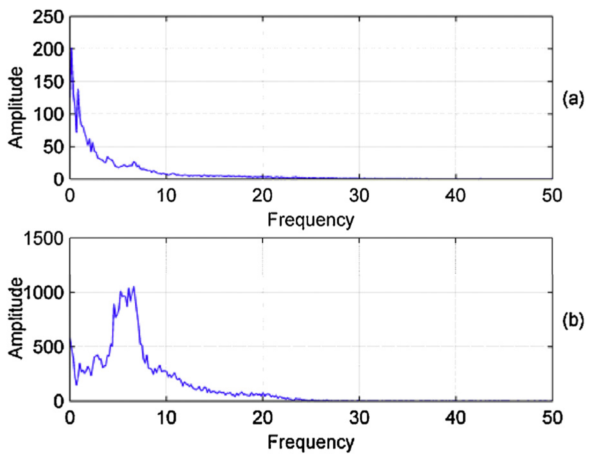

Fig. 4. HMS of (a) seizure EEG signal and (b) nonseizure EEG signal.

2.4.2. Sub-band energies

The energy features are effective features for epileptic seizure detection [30,31]. The energy features based on the frequency-bands of the rhythms in EEG signals (namely delta: 0–4 Hz; theta: 4–8 Hz; alpha: 8–12 Hz; beta: 12–30 Hz; gamma: 30–50 Hz) are extracted [32]. The energy distribution between seizure and nonseizure EEG signal is quite different [31]. The energy of a normal EEG signal is contained mostly in the delta wave, while the same wave in the seizure one accounts for a small proportion of total energy. Thus, it is distinctive to use sub-band energy for classification of EEG signals. It should be noted that the energy of HMS has different meaning with Fourier spectrum. The sub-band energy is defined as the summation of the magnitude of squared spectrum components [11]:

$$e_i = \sum_{f=0}^{k-1} h_i^2 \tag{15}$$

where h_i is the ith sub-band of the spectrum and k is the total number of frequency in each band. Thus, the energy feature vector can be formed with the five features as $E=[e_1, e_2, e_3, e_4, e_5]$.

3. Results and discussion

This section presents the experiment results with the method. Comparisons with the Fourier spectrum analysis method and method presented by Polat [3] are done to show the effectiveness of this technique.

The HHT method is applied to the EEG signals, and then the HMS can be obtained. Fig. 4(a) and (b) shows the plots of the HMS analysis method applied to typical seizure and nonseizure EEG signals with the frequency resolution of 512, respectively. It is clearly observed from the figures that the amplitude and the distribution of the frequency of seizure and nonseizure EEG signals are quiet different. Next with these obtained spectrums, the energy can then be calculated from each sub-bands corresponding to the frequency rhythms of EEG signal.

The class discrimination ability of the three entropies and five sub-band energy features is quantified using *t*-test. The *t*-test assesses whether the distribution means of two groups are statistically different from each other. Fig. 5(a)–(c) shows the relative entropy distribution of Shannon, Renyi and Tsallis of seizure and nonseizure EEG signals, respectively and the statistical values of the three kinds of entropies of the two class are presented in Table 1. Relatively, the values of spectral entropies of seizure EEG signal are larger than that of nonseizure, which mean that the spectrum

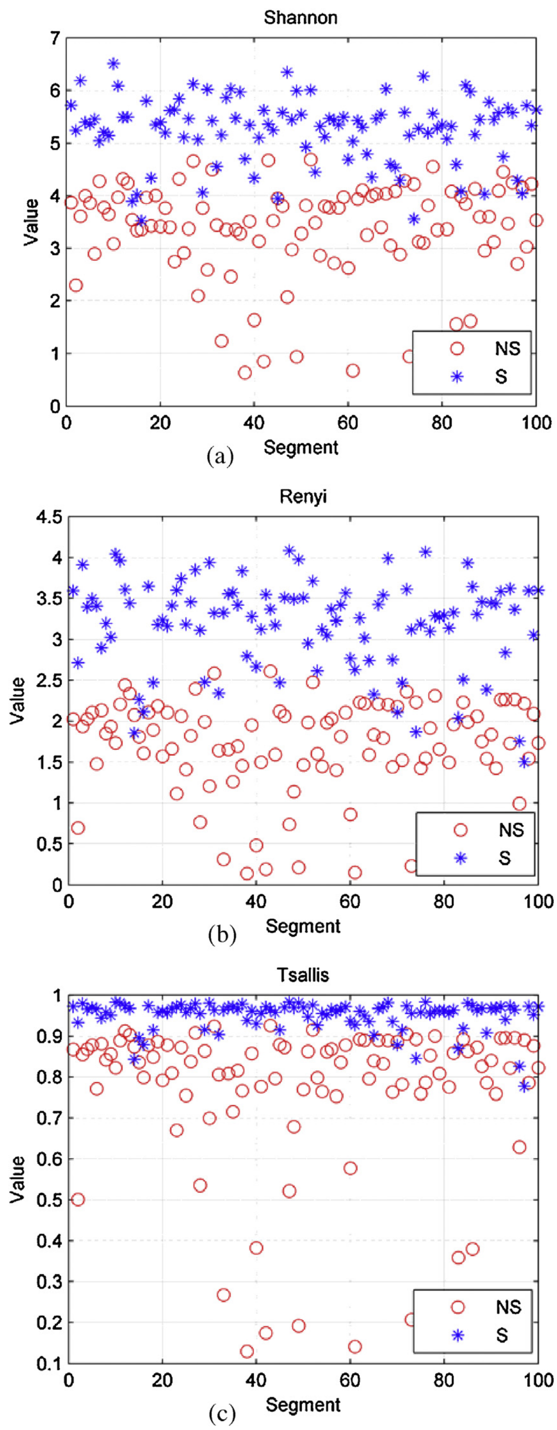

Fig. 5. Entropy distribution of Shannon (a), Renyi (b) and Tsallis (c) of seizure (S) and nonseizure (NS) EEG signals.

Table 1
Statistical values of Shannon, Renyi and Tsallis spectral entropy of seizure and nonseizure EEG signals.

	Mean			Std		
	Shannon	Renyi	Tsallis	Shannon	Renyi	Tsallis
Seizure	5.2405	3.1803	0.9504	0.6337	0.5571	0.0361
Nonseizure	3.3424	1.6673	0.7646	0.9372	0.6087	0.1942

Table 2
p-Value of the extracted features.

	Entropies			Waveforms				
	Shannon	Renyi	Tsallis	Delta	Theta	Alpha	Beta	Gamma
p-Value	0	0	0	0	0	0	8.32E−8	0.0027

Table 3
Experiment results for 10 independent executions for each problem with two kinds of methods.

	Hilbert marginal spectrum		Fourier spectrum	
	A–E (c = 5.70, g = 85.36)	ABCD–E (c = 89.75, g = 16.60)	A–E (c = 42.34, g = 27.30)	ABCD–E (c = 71.31, g = 13.72)
Standard deviation	0.3375	0.3887	0.4216	0.2459
Average accuracy	99.85%	98.80%	99.30%	98.16%

Table 4
Comparative results with the state of the art.

Problem	Author	Method	Accuracy
A–E	Nigam et al. [39]	Nonlinear preprocessing filter, diagnostic artificial neural network	97.2
	Srinivasan et al. [2]	Time-frequency domain features, recurrent neural network	99.6
	Polat et al. [3]	FFT-decision tree classifier	98.72
	Subasi [40]	Discrete wavelet transform, mixture of expert model.	95
	Guo et al. [41]	Discrete wavelet transform-relative wavelet energy, MLPNN	95.2
	Wang et al. [42]	Wavelet transform and Shannon entropy, kNN	99.45
	Nicolaou et al. [43]	Permutation entropy, SVM	93.55
	Fu et al. [20]	Time-frequency image using HHT, SVM	99.13
	This work	HMS analysis, SVM	**99.85**
ABCD–E	Tzallas et al. [7]	Time-frequency analysis, artificial neural network	97.73
	Guo et al. [5]	Multiwavelet transform, MLPNN	98.27
	Rivero et al. [44]	Time frequency analysis, kNN	98.40
	Kaleem et al. [45]	Variation of empirical mode decomposition	98.2
	This work	HMS analysis, SVM	**98.80**

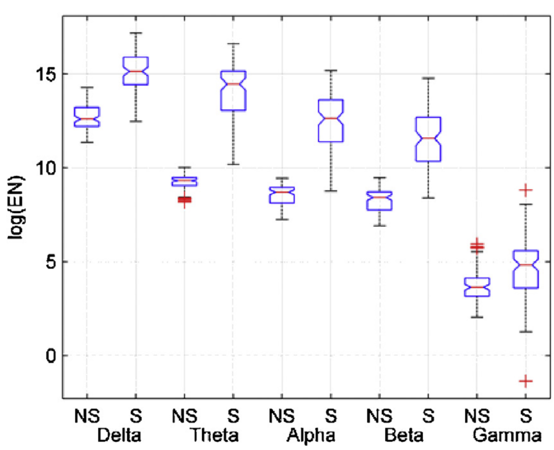

Fig. 6. Box plot of each sub-band energy features of seizure (S) and nonseizure (NS) EEG signals.

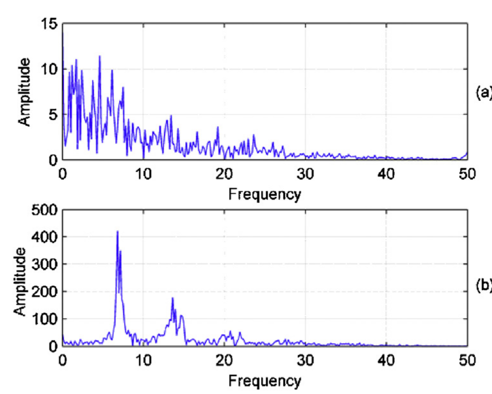

Fig. 7. Fourier spectrum of (a) seizure EEG signal and (b) nonseizure EEG signal.

probability distributions of seizure are more broad and flat. Fig. 6 illustrates the box plot of all the five sub-band energy features of seizure and nonseizure EEG signals. Besides, the *p*-values of the features used in test are presented in Table 2. It can be clearly observed that the three entropies and the first four sub-band energy features are statistically significant ($p < 0.0001$).

However, using only the *t*-test for classification may not be completely correct about the type of signals being classified, here SVM with RBF kernel is used as a classifier to obtain accurate classification of seizure and nonseizure EEG signals. SVM was initially developed as a binary classifier and thus it has a great advantage in binary classification problems such as seizure detection [33–35]. The RBF kernel is used since it can nonlinearly map the data into a higher dimensional feature space. Furthermore, the linear kernel is a special case of RBF [36]. In addition, the sigmoid kernel behaves like RBF for certain parameters [37].

In order to further assess the performance of the proposed method for seizure detection, the Fourier spectrum analysis method with the same dataset is conducted for comparison in this experiment. The Fourier spectrum of the seizure and nonseizure EEG signal is presented in Fig. 7(a) and Fig. 7(b) respectively. For a valid comparison, the EEG signal which is plotted in Fig. 7(a) is the same signal plotted in Fig. 4(a) as well as Fig. 7(b) and Fig. 4(b). It should be noted that they have the same frequency resolution. A visual comparison between Fig. 4 and Fig. 7 can give us a qualitative discrimination about the difference of the two methods. It is obvious that the HMS suffers from less leakage than the Fourier spectrum. The direct reason of this leakage is because of the different interpretation of the two spectrums mentioned in the above section.

Table 3 shows the classification performance of the SVM classifier with two kinds of analysis method for A–E and ABCD–E problems. The parameter (c, g) of RBF kernel is determined by using genetic algorithm (GA) [38]. The parameters of the GA are determined by setting the maximum evolution algebras to 200 and the maximum populations to 20, using 5-fold cross validation [20,38]. It should be highlighted that the classification accuracy is valuated using 10-fold cross-validation and then repeated 10 times. It is obvious that the classification accuracy obtained by the method of HMS analysis can reach 99.85% which is higher than the Fourier spectrum analysis method in A–E problem with the same classifier. In [3], the authors adopted fast Fourier transform based Welch method for feature extraction and decision tree for classifying, and the best classification accuracy obtained by them is 98.72%. In addition, the results presented herein were compared with other works reported in recent years. In Table 4, it is clear that the proposed system achieves better results than the rest of the works. In general, the method of HMS analysis can provide a more appropriate representation than that of Fourier spectrum when processing with nonlinear and nonstationary signals, such as EEG signal.

4. Conclusions

The HHT is a creative and useful method in signal analysis, especially the marginal spectrum analysis method. The paper proposes signal analysis and feature extraction for seizure detection in the Hilbert marginal spectrum domain. The marginal spectrum analysis is quite different from Fourier spectrum analysis, as the frequency in the marginal spectrum indicates only the likelihood that an oscillation with such a frequency exists. In this paper, the spectral entropies and sub-band energy features have been extracted from the Hilbert marginal spectrum and the efficient ones have been used as input of the SVM to classify seizure and nonseizure EEG signals. The classification results indicate that the method of marginal spectrum provides higher classification accuracy than that of Fourier spectrum analysis. Although from the results, it seems that the proposed method is not significantly better than the Fourier one. However, because the classification results relate to dataset, feature extraction and learning algorithm apart from the signal analyzing methods, we still think it is a potential method to detect seizure in EEG signals. In addition, it should be worth to mention here that the proposed technique could also be applied in other environments involving EEG signals, such as sleep stage classification and brain-computer interface (BCI) application where significant improvements in classification accuracy may be possible.

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