Automatic Seizure Detection Using Wavelet Transform and SVM in Long-Term Intracranial EEG

Yinxia Liu, Weidong Zhou, Qi Yuan, and Shuangshuang Chen

***Abstract*—Automatic seizure detection is of great significance for epilepsy long-term monitoring, diagnosis, and rehabilitation, and it is the key to closed-loop brain stimulation. This paper presents a novel wavelet-based automatic seizure detection method with high sensitivity. The proposed method first conducts wavelet decomposition of multi-channel intracranial EEG (iEEG) with five scales, and selects three frequency bands of them for subsequent processing. Effective features are extracted, such as relative energy, relative amplitude, coefficient of variation and fluctuation index at the selected scales, and then these features are sent into the support vector machine for training and classification. Afterwards a postprocessing is applied on the raw classification results to obtain more accurate and stable results. Postprocessing includes smoothing, multi-channel decision fusion and collar technique. Its performance is evaluated on a large dataset of 509 h from 21 epileptic patients. Experiments show that the proposed method could achieve a sensitivity of 94.46% and a specificity of 95.26% with a false detection rate of 0.58/h for seizure detection in long-term iEEG.**

***Index Terms*—Electroencephalogram (EEG), seizure detection, support vector machine (SVM), wavelet transform.**

I. Introduction

EPILEPSY is a common chronic neurological disorder characterized by the sudden, usually brief, excessive electrical discharges in a group of brain neurons [1]. More than 50 million people are diagnosed with epilepsy in the world [2]. Electroencephalogram (EEG) signal analysis is widely used for assessing disorders of brain function, especially for epilepsy diagnosis. The traditional method used to identify seizures is heavily dependent on the visual analysis of the EEG recordings by the trained professionals [3]. This is a very costly as well as tedious task to review a 24-h continuous EEG recording, particularly if the number of EEG channels increases. Automating the detection of epileptic seizures is valuable for assisting neurologists to analyze the EEG recordings, and could also offer solutions for closed-loop therapeutic devices such as implantable electrical stimulation systems [4].

Automatic seizure detection methods in the diagnosis of epilepsy were developed in the early 1970s. In recent years, many algorithms for the detection of seizures have been proposed and applied, such as frequency domain analysis [5], time-frequency domain analysis [6], [7], artificial neural network based analysis [8], [9], and machine learning based analysis [10]. For nonstationary EEG signals, time-frequency analysis method, such as discrete wavelet transform (DWT), has been proved to be an effective analysis tool and could give quantitative evaluation of ictal EEG in different frequency bands.

Selecting effective features which can best represent the characteristics of the EEG signals is important in seizure detection. A number of features have been investigated based on wavelet features [6], [11], amplitude relative to background activity [12], energy [13], Lyapunov exponents [14], and entropy [15], [16], etc.

A good classifier is essential for an excellent seizure detection method. Support vector machine (SVM) based on statistical learning theory and structural risk minimization is regarded as a powerful tool for pattern recognition [17] [18]. Due to its good generalization ability, SVM has been widely used for pattern classification [19], [20].

In this study, an algorithm based on DWT is proposed for detection of seizures from the long-term intracranial EEG signals. The iEEG epochs were decomposed into five frequency bands using wavelet transform with five scales and three frequency bands at scales 3, 4, and 5 were selected for subsequent processing. Fluctuation index is proposed as a novel iEEG feature, which is sensitive to signal variations of frequency and amplitude. The statistical parameters such as fluctuation index, relative energy, relative amplitude, coefficient of variation are computed within the selected three frequency bands. SVM classifier is employed for seizure classification. Finally, postprocessing including smoothing, multi-channel decision fusion and collar technique is applied to obtain more accurate and stable classification results.

II. Intracranial EEG Dataset

The intracranial EEG data used in this study came from the Epilepsy Center of the University Hospital of Freiburg, Germany [21]. The database contains iEEG from 21 patients with a total of 87 seizures. The data were recorded during presurgical epilepsy monitoring with invasive electrodes. There are 24–26 h of nonseizure data and 2–5 h of seizure data for each patient. Six contacts were selected, three (channel 1, 2, 3) near the epileptic focus and three (channel 4, 5, 6) in remote locations involved in seizure spread and propagation. Seizure onset and offset times were determined by the experts based on intracranial EEG recordings. In order to obtain a high signal-to-noise ratio and fewer artifacts, the iEEG data acquisition was performed with a Neurofile NT digital video EEG system, with

Manuscript received January 11, 2012; revised March 24, 2012 and May 27, 2012; accepted June 15, 2012. Date of publication July 31, 2012; date of current version November 02, 2012. This work was supported in part by the Development Program of Science and Technology of Shandong under Grant 2010GSF10243 and in part by the Independent Innovation Foundation of Shandong University under Grant 2009JC004.

The authors are with the School of Information Science and Engineering, Shandong University, Jinan 250100, China (e-mail: yxliu@mail.sdu.edu.cn; wdzhou@sdu.edu.cn; qiyuan@mail.sdu.edu.cn; css000248@163.com).

Digital Object Identifier 10.1109/TNSRE.2012.2206054

TABLE I
DISTRIBUTION OF THE SAMPLES IN THE TRAINING AND TEST DATA SETS

	non-seizure	seizure	Total	Time (s)
Training	105	105	210	840
Test	69753	2359	72112	288448

a sampling rate of 256 Hz, and a 16 bit analog to digital converter. The iEEG datasets were preprocessed by a 50-Hz notch filter and a band pass filter between 0.5 and 120 Hz.

A. Training Data

There are 105 segments of nonseizure data and 105 segments of seizure data selected for training from the total 21 patients. Each segment contains 1024 points (256 points = 1 s) and the overall time length of the training segments is 840 s. The seizure/nonseizure segments in training data set were randomly chosen from the seizure/nonseizure parts marked by the EEG experts.

B. Testing Data

In total, 80.14 h of iEEG data containing 82 seizures in 21 patients were selected as test data. There are 2359 segments of seizure and 69 753 segments of nonseizure, and the length of each segment is 1024 points too. Training data and test data are shown in Table I.

III. FEATURE EXTRACTION

The wavelet transform (WT) has been developed into an important tool in feature extraction and nonstationary signal analysis. WT employs long time windows for more precise low frequency information, and short time intervals for high frequency information. It has been justified in [22] that the wavelet transform had better resolution and high performance for representation and visualization of the epilepsy activity than the short-time Fourier transform. So we chose discrete wavelet transform (DWT) for EEG feature extraction. DWT could analyze the signal at different frequency bands with different resolutions through decomposing the signal into a coarse approximation $(c_{j,k})$ and detail information $(d_{j,k})$. The wavelet coefficients can be calculated by

$$c_{j,k} = \langle f(t), \phi_{j,k}(t)\rangle = \int_R f(t)2^{\frac{-j}{2}}\overline{\phi(2^{-j}t-k)}dt \quad (1)$$

$$d_{j,k} = \langle f(t), \psi_{j,k}(t)\rangle = \int_R f(t)2^{\frac{-j}{2}}\overline{\psi(2^{-j}t-k)}dt \quad (2)$$

where $\psi(t)$ is the mother wavelet, $\phi(t)$ is the basic scaling, j is the scale index, and k is the translation parameter. Inverse discrete wavelet transform is given by

$$f(t) = \sum_k c_{j,k}2^{\frac{-j}{2}}\phi(2^{-j}t-k) + \sum_k d_{j,k}2^{\frac{-j}{2}}\psi(2^{-j}t-k). \quad (3)$$

Selecting a wavelet which has the similar shape and frequency characteristics with seizures is also essential. As presented in [6], [23], and [24], Daubechies-4 (db4) wavelet was used for seizure detection. The smoothing feature of the db4 wavelet made it more appropriate to detect changes of iEEG signals, and db4 wavelet was selected in the present study. The iEEG signals with sampling rate of 256 Hz were decomposed into five scales, giving the approximation coefficients representing 0–4 Hz (a5) and detail coefficients representing 64–128 Hz (d1), 32–64 Hz (d2), 16–32 Hz (d3), 8–16 Hz (d4), and 4–8 Hz (d5). Although seizures have a much broader spectrum, seizures in recorded EEGs mainly occur between 3 and 29 Hz [24]. Therefore, the wavelet scales 3, 4, and 5 could represent the ictal iEEG frequency range, and the detail coefficients starting from d3 to d5 were chosen to extract iEEG features which are relative energy, relative amplitude, coefficient of variation, and fluctuation index. Fig. 1 shows the details (d1–d5) of iEEG with normal and seizure signals respectively. The seizure discharge is mostly visible in scales 3, 4, and 5.

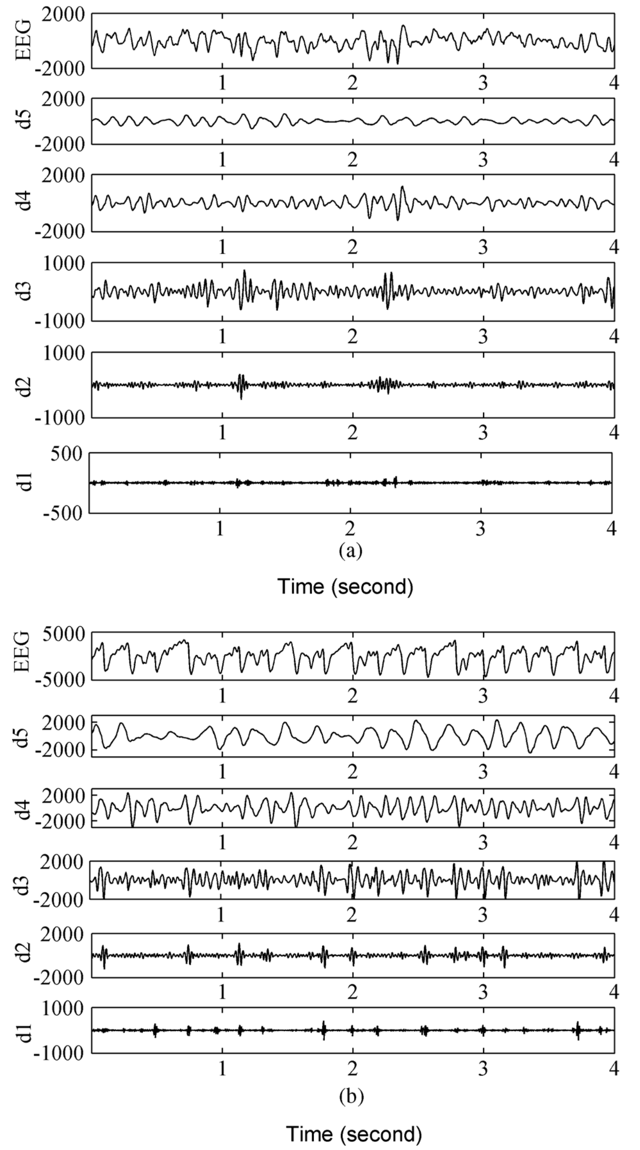


Fig. 1. Decomposition of EEG by DB4 wavelet into details (d1–d5) signals. (a) Normal signal. (b) Seizure signal.

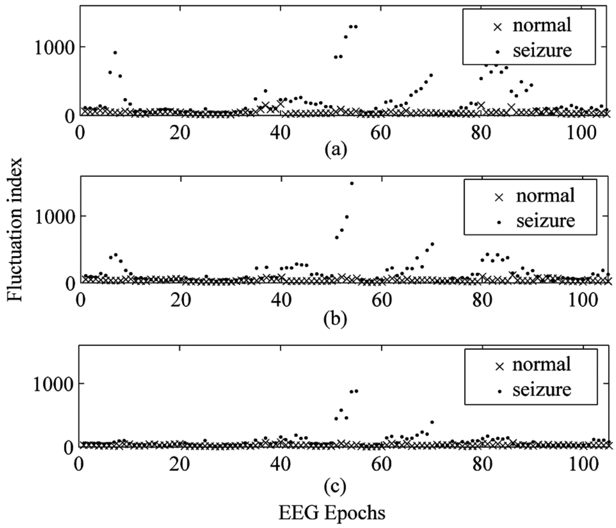


Fig. 2. The differences of fluctuation index (FI) between normal and seizure EEG signals. (a) The FI values of the D3 coefficients. (b) The FI values of the D4 coefficients. (c) The FI values of the D5 coefficients.

A. Relative Energy

The relative energy indicates the strength of the signal as it gives the area under the curve of power at any interval of time. For the Daubechies wavelet, the sum of square of coefficients of the wavelet series is the energy of the EEG signal [6]. The energy of EEG signal with limited length is given by

$$E(l) = \sum_{i=1}^{N} D_i^2 * \tau / N \tag{4}$$

where τ is the sampling interval and N is the number of DWT coefficients D_i presented at scale l. The relative energy $E_r(l)$ of the scale l is computed as

$$E_r(l) = \frac{E(l)}{\sum\limits_{i=1}^{S} E(i)} \tag{5}$$

where S is the number of the wavelet scales.

B. Relative Amplitude

Since the majority of seizure activity is paroxysmal, the amplitude relative to the background would increase when the seizure occurs [25]. The average amplitude of an epoch was computed as the mean of the amplitudes of the segments obtained after the half wave decomposition [26]. In order to get the amplitude relative to the background, each iEEG epoch is normalized by the amplitude of the background in the corresponding scale. The background was defined as 120 s of data after leaving a gap of 60 s to the epoch being analyzed. The analysis results show that relative amplitude values can clearly discriminate between normal and seizure iEEG time series, and large relative amplitude values usually accompany with seizures.

C. Coefficient of Variation

The standard deviation (σ) shows how closely various features are near to the mean value (μ). We use mean value to measure the mean amplitude. The coefficient of variation (V_c) can measure the variations of the signal amplitude. The variance of each decomposed subband can form a feature vector. Since the epileptic signal exhibiting rhythmic behavior of regular amplitude, the coefficient of variation in general gives smaller values than that during the interictal times [6]. The corresponding coefficient of variance can be expressed as

$$Vc(l) = \left(\frac{\sigma(l)^2}{\mu(l)^2}\right) \tag{6}$$

where

$$\mu(l) = (1/N)\sum_{i=1}^{N} D_i$$

and

$$\sigma(l) = \sqrt{(1/N)\sum_{i=1}^{N}(D_i - \mu(l))^2}.$$

N is the number of DWT coefficients D_i at scale l.

D. Fluctuation Index

The ictal iEEG commonly displays larger fluctuations than the interictal. The fluctuation index (FI) is proposed to measure the intensity of iEEG signal changes. The FI of scale l is defined as

$$FI(l) = \frac{1}{N}\sum_{i=1}^{N} |D_{i+1} - D_i| \tag{7}$$

where N is the number of DWT coefficients D_i at scale l. Fig. 2 shows the difference of fluctuation index between normal and seizure iEEG signals. It could be found that the fluctuation index of the iEEG during seizures usually becomes greater than that during the nonseizure periods.

IV. Support Vector Machine

The SVM built on statistical learning theory was developed by Cortes and Vapnik (1995) for binary classification, and is now widely used in pattern classification [10], [17]. The idea of SVM algorithm is to project nonlinear separable samples onto another higher-dimensional space by kernel functions, and then locate the optimal separating hyperplane (OSH) in the projection space by solving a quadratic optimization problem [27], [28]. Typical kernel functions of SVM are linear kernel, polynomial kernel, radial basis functions (RBF), and sigmoidal neural network kernel. In this study, satisfactory results were achieved by using RBF kernel function, which is defined by $K(x, y) = \exp(-|x - y|^2/2\sigma^2)$.

V. Postprocessing

In this paper, the value of the SVM output was defined as 1 or -1, which 1 represents the normal/non-seizure iEEG and -1 represents the seizure iEEG. But the value of the SVM output is not always 1 or -1, usually changing in the interval $[-1\ 1]$. For this reason, postprocessing for the SVM outputs is necessary. The postprocessing scheme consists of smoothing, multi-channel decision fusion, and collar technique.

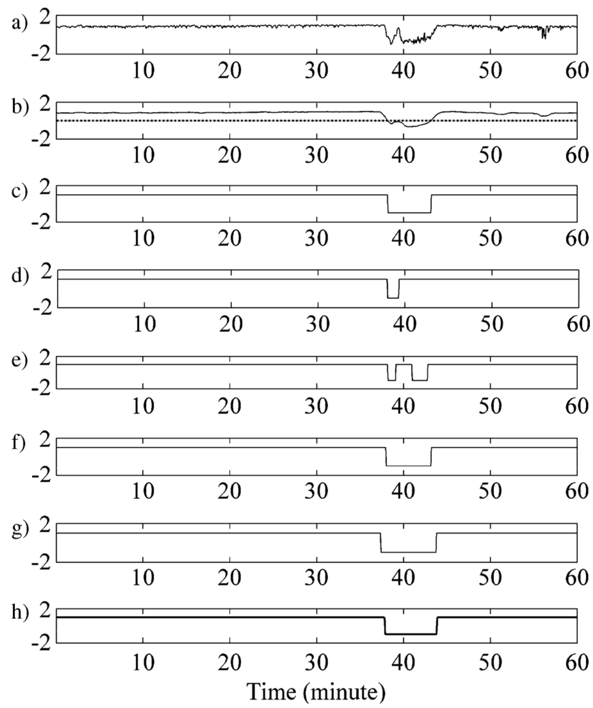


Fig. 3. The postprocessing scheme for patient 14 during the seizure at the 17th hour. (a) The raw detection output of the SVM classifier with channel 1. (b) The smoothed output after the moving average filtering. (c) The binary decisions with channel 1 after thresholding. (d) The binary decisions with channel 2 after thresholding. (e) The binary decisions of channel 3 after thresholding. (f) The binary decisions when three channels are fused. (g) The final binary decisions after the collar operation, which increases the duration of all positive decisions. (h) The ground truth, where -1 indicates seizure.

Firstly, a central linear moving average filter (MAF) is applied to the SVM outputs in each channel [Fig. 3(a)]. The moving average filter is an effective filter for reducing random noise, while keeping the sharpest step response [29]. MAF achieves this using the mean of a number of points from the input signal to replace each point in the output signal. The average value is then compared to a threshold [Fig. 3(b)]. After experiments with the training data, we found that zero is a relatively good threshold for each patient. So we select zero as the threshold.

After comparison, binary decisions are taken per channel [Fig. 3(c)–(e)]. In order to reduce false positive rates, multi-channel decision is necessary. To be qualified as a seizure, the data need to be identified as following: if the seizures are detected at least in two channels simultaneously, the whole epoch will be marked as "seizure;" if the seizure is detected just in one channel, the epochs before or after current epoch in the same channel will be used to determine whether the current epoch is a seizure. If the adjacent epoch has been marked as seizure, then current epoch will be labeled as "seizure." Otherwise it is denoted as nonseizure. This process is shown in Fig. 3(f) as an example in which the binary decision from three channels [Fig. 3(c)–(e)] are fused.

Since the beginning and the end of seizures are step by step changing, the characteristics of iEEG signal are gradually increased or reduced, rather than a sudden dramatic change. In addition, under the impact of smoothing, the beginning or end stage of seizure would normally be mistaken as interictal. The collar technique used to prevent cutting off the beginning and ending of words [30] is applied to extend seizure decision in detecting preseizure and postseizure parts [Fig. 3(g)]. So that the misjudgment of the beginning or end stage of seizure can be reduced. Fig. 3 shows the whole procedure of postprocessing.

VI. Results

To test our seizure detection algorithm, we divided all iEEG recordings from each patient into a randomly selected training and test set. The training and test data were shown in Table I. These training data were used to train the classifier and the test data were used to assess the performance of the algorithm. The classification implementation procedure is as follows: firstly, iEEG signal is decomposed into subsignals through DWT with five-scale decomposition. Since the seizures in recorded iEEGs usually occur between 3 and 29 Hz, the decomposition detail coefficients starting from d3 to d5 are chosen. After that, the features including relative energy, relative amplitude, coefficient of variation, and fluctuation index are calculated for each sub-scale signals d3–d5 to form a feature vector with a dimension of 12. Then, the generated feature vector is fed into SVM to classify normal/nonseizure and seizure iEEGs. Finally, the postprocessing is applied.

After postprocessing, the performance of the proposed seizure detection system has been assessed at the segment-based level by comparing the results of nonseizure/seizure labels assigned to iEEG segments by the system and the expert. The performance of automatic seizure detection algorithm has been computed based on the following statistical measures [6].

1) Sensitivity: Number of true positives/the total number of seizure segments labeled by the EEG experts. True positive represents a detected seizure segment by the algorithm was also identified as seizure by the EEG experts.
2) Specificity: Number of true negatives/the total number of nonseizure segments labeled by the EEG experts. True negative represents a segment labeled as nonseizure both by the algorithm and by the EEG experts.
3) Recognition accuracy: Number of correctly identified segments/total number of segments.
4) False detection rate: Number of false detections/hour.

Table II shows the results of seizure onsets detection in each patient by using our proposed method. The sensitivity of our algorithm varied from 50% to 100% with 18 patients having sensitivities above 90%. On average, the sensitivity of 94.46%, the accuracy of 95.33% and the specificity of 95.26% were obtained. Patient 1 had the lowest sensitivity of 50%, mostly because half of the seizure durations were less than 12 s. For the seizure data of patient 10 because of electrode disconnection and reconnection there were sharp jumps in voltage which are falsely detected as seizure by the system. For the seizure data of patient 11 the authors could not find any seizure spikes by visual inspection. In this study, 82 seizures were used to test our algorithm and 79 seizures were detected correctly. Only three short length seizures for patient 1 and patient 11 were missed. The average detection latency between the seizure onsets marked by the expert and the system was 11.1 s.

TABLE II
DETECTION PERFORMANCE OF THE PROPOSED ALGORITHM

Patient number	Seizure Type	Accuracy (%)	Sensitivity (%)	Specificity (%)	False detection rate (/h)	Number of seizure segments	Number of total segments	FN	FP
1	SP,CP	99.56	50	99.67	0.25	13	3600	4	12
2	SP,CP,GTC	99.74	100	99.73	0	89	2700	0	7
3	SP,CP	92.36	98.67	92.13	1.19	116	3770	2	110
4	SP,CP,GTC	92.53	100	92.34	1.2	110	4500	0	336
5	SP,CP,GTC	98.02	98.95	98.05	0.2	56	4500	2	87
6	CP,GTC	96.89	100	96.82	1	51	2700	0	84
7	SP,CP,GTC	91.41	97.92	90.96	0.33	116	2700	5	227
8	SP,CP	100	100	100	0	45	517	0	0
9	CP,GTC	89.64	91.05	90.05	0.8	143	4500	30	436
10	SP,CP,GTC	81.69	93.40	79.66	1.61	476	3333	61	575
11	SP,CP,GTC	94.06	72.75	94.25	0.75	158	3600	19	195
12	SP,CP,GTC	99.75	100	99.75	0	55	3600	0	9
13	SP,CP,GTC	91	100	90.77	0.5	79	1800	0	162
14	CP,GTC	98.97	99.72	98.93	0	216	3600	1	36
15	SP,CP,GTC	92.75	84.62	93.91	0.5	145	3600	48	213
16	SP,CP,GTC	98.24	98.1	98.27	0	151	4218	4	64
17	SP,CP,GTC	99.51	99.17	99.52	0	108	4500	1	21
18	SP,CP	98.43	100	98.42	2.03	8	1774	0	28
19	SP,CP,GTC	94.78	100	94.75	0.75	13	3600	0	188
20	SP,CP,GTC	96.73	100	96.66	0.4	106	4500	0	147
21	SP,CP	95.84	99.33	95.77	0.6	105	4500	1	186
Mean	-	95.33	94.46	95.26	0.58	112	3434	8	149

SP: simple partial seizure, CP: complex partial seizure, and GTC: generalized tonic-clonic seizure. FP: false-positives, FN: false-negatives

VII. DISCUSSION AND CONCLUSION

The 21-patient Freiburg iEEG database has been used in several studies for developing seizure detection methods in depth EEG [31]–[34]. All those iEEG data were recorded using a Neurofile NT digital video-EEG system with 256 Hz sampling rate, and a 16 bit analog-to-digital converter, from grid-, strip-, and depth-electrodes surgically inserted inside the brain or placed on the cortex of the patients. Majumdar (2011) used the differential windowed variance method on the same iEEG database with 15 patients containing 59 h of seizure, and the sensitivity of his method reached 91.525% [31]. Aarabi *et al.* (2009) developed an automated tool that used the fuzzy rule-based method for all patients with 78 seizures. At the segment-based level, the system yielded a sensitivity of 68.9% [32]. Chua (2011) proposed a patient specific seizure detection system which has been tested on 63 seizures from 15 subjects. The sensitivity of 78% was obtained [33]. Raghunathan (2011) proposed multistage seizure detection which detected morphologies of electrographic seizures characterized by high-frequency, lower-amplitude onsets progressing on to larger amplitudes with a downward shift in the dominant frequency. The average sensitivity was found to be 87.5% for five patients with 24 seizures [34]. In comparison to the previous systems, the sensitivity (94.46%) of our proposed algorithm is much better. Table III presents a comparison on the results between our proposed method and the other methods.

TABLE III
COMPARISON OF BEST PERFORMANCE FOR DIFFERENT METHODS

Method	Sensitivity (%)	Number of seizures selected
Differential Windowed Variance[31]	91.525	59
A fuzzy rule-based system[32]	68.9	78
Patient specific seizure detection[33]	78	63
Multistage seizure detection[34]	87.5	24
Our proposed algorithm	94.46	82

Recently, many seizure detection and EEG classification tools based on wavelet algorithm have been developed with different degree of success [6], [35]–[37]. Khan and Gotman developed a seizure detection method for intracerebral monitoring using features of relative energy, coefficient of variation and relative amplitude [6]. They selected Daubechies-4 wavelet after testing other conventional wavelets. The method was evaluated on long-term EEG data from 11 patients, including 229 h and 66 seizures, and achieved a sensitivity of 87%. Compared to their system, our proposed approach yielded a higher sensitivity.

Zurjum proposed a discrete wavelet transform based seizure detection method with ANN as a classifier [35]. The number of zero-crossings, the average distance between adjacent zero-crossings, the number of extrema, and the average distance between adjacent extrema of the wavelet coefficients (WCs) of nine scales were extracted to form a feature set. In this study, EEG data from five neonates with less than 20 min recordings for each patient time were manually segmented into seizures and nonseizures as the training and test data. The obtained results show that on the average 95% of the EEG seizures were classified [35]. Mihandoost presented a set of statistic feature for EEG classification using Daubechies 4 wavelet transform [36]. Three statistical features, fourth moment divided by second moment, difference between maximum and minimum and zero-crossing of the wavelet coefficients were extracted as three statistical features. Three category short-term EEG segments from five healthy volunteers and five epilepsy patients during seizure-free interval and seizure were employed for classification test. Their system yielded a correct classification rate of 98.17% [36]. Chang proposed another scheme to detect epileptic seizure in the grouped multi-channel EEG signals using independent component analysis (ICA) and wavelet transform [37]. The short-term EEG data were collected from five patients with epilepsy, and divided into small segments manfully, each 0.3 s. In a total, they obtained 2400 segments (about 12 min recordings), where 345 segments were epileptic seizure. Their system yielded a good performance for classifying seizure and no-seizure EEG segments [37]. However, the successes of those above approaches depend on the use of short-term EEG for evaluation. This limits the clinical applicability of those approaches, and their systems should be further assessed on long-term EEG data so as to confirm their effectiveness for seizure detection.

As we know, selecting suitable features can improve the efficiency of classifier. Although amplitude, duration and shape of waveforms features can make a distinction between normal and seizure segments, high variability of background EEGs and seizure characteristics make it indispensable to make use of the statistical and relative values of these features. We have found that the proposed method can obtain high performance in the automatic seizure detection only if an appropriate subset of uncorrelated features is extracted. Combination of the four features such as relative energy, relative amplitude, coefficient of variation, and fluctuation index turns out to be strong separability for different types of background activities and seizures.

Our proposed method for the automatic seizure detection in depth EEG provides high sensitivity and accuracy by using DWT and SVM. The DWT is applied to nonstationary processes with the advantages both in the time and frequency domains. SVM has been demonstrated many unique advantages in resolving small sample, nonlinear and high dimensional pattern recognition. We choose the relative energy, relative amplitude, coefficient of variation, and fluctuation index as features and then input them into the SVM for recognition. Finally, the postprocessing was applied to the SVM outputs. Experimental results show that our proposed method is effective and applicable. In order to fit the user's specific needs, the parameters of our algorithm, i.e., the length of MAF, are tunable which allow for the adjustment of the detection performance. How to set the parameters automatically so as to improve the detection efficiency further will be done in a forthcoming study.

References

[1] S. Sanei and J. A. Chambers, *EEG Signal Processing*. New York: Wiley, 2007.

[2] S. Santaniello, S. P. Burns, A. J. Golby, J. M. Singer, W. S. Anderson, and S. V. Sarma, "Quickest detection of drug-resistant seizures: An optimal control approach," *Epilepsy Behav.*, vol. 22, pp. 49–60, 2011.

[3] H. Adeli, Z. Zhou, and N. Dadmehrc, "Analysis of EEG records in an epileptic patient using wavelet transform," *J. Neurosci. Methods*, vol. 123, no. 1, pp. 69–87, 2003.

[4] Y. Tang and D. M. Durand, "A tunable support vector machine assembly classifier for epileptic seizure detection," *Expert Syst. Appl.*, vol. 39, pp. 3925–3938, 2012.

[5] J. Gotman and P. Gloor, "Automatic recognition and quantification of interictal epileptic activity in the human scalp EEG," *Electroencephalogr. Clin. Neurophysiol.*, vol. 41, pp. 513–529, 1976.

[6] Y. U. Khan and J. Gotman, "Wavelet based automatic seizure detection in intracerebral electroencephalogram," *Clin. Neurophysiol.*, vol. 114, pp. 898–908, 2003.

[7] B. Boashash, M. Mesbah, and P. Coldtiz, "Time-Frequency Detection of EEG Abnormalities," in *Time-Frequency Signal Analysis and Processing: A Comprehensive Reference*, B. Boashash, Ed. Oxford, U.K.: Elsevier, 2003, pp. 663–670.

[8] A. J. Gabor, "Seizure detection using a self-organizing neural network: Validation and comparison with other detection strategies," *Electroencephalogr. Clin. Neurophysiol.*, vol. 107, pp. 27–32, 1998.

[9] W. R. Webber, B. Litt, K. Wilson, and R. P. Lesser, "Practical detection of epileptiform discharges (EDs) in the EEG using an artificial neural network: A comparison of raw and parameterized EEG data," *Electroencephalogr. Clin. Neurophysiol.*, vol. 91, pp. 194–204, 1994.

[10] A. Subasi and M. I. Gursoy, "EEG signal classification using PCA, ICA, LDA and support vector machines," *Expert Syst. Appl.*, vol. 37, no. 12, pp. 8659–8666, 2010.

[11] A. Subasi, "EEG signal classification using wavelet feature extraction and a mixture of expert model," *Expert Syst. Appl.*, vol. 32, no. 4, pp. 1084–1093, 2007.

[12] A. Murro, D. King, J. Smith, B. Gallagher, H. Flanigin, and K. Meador, "Computerized seizure detection of complex partial seizures," *Electroencephalogr. Clin. Neurophysiol.*, vol. 79, no. 4, pp. 330–333, 1991.

[13] H. Qu and J. Gotman, "A patient-specific algorithm for the detection of seizure onset in long-term EEG monitoring: Possible use as a warning device," *IEEE Trans. Biomed. Eng.*, vol. 44, no. 2, pp. 115–122, Feb. 1997.

[14] N. Güler, E. Übeyli, and I. Güler, "Recurrent neural networks employing Lyapunov exponents for EEG signals classification," *Expert Syst. Appl.*, vol. 29, no. 3, pp. 506–514, 2005.

[15] N. Kannathal, M. Choo, U. Acharya, and P. Sadasivan, "Entropies for detection of epilepsy in EEG," *Comput. Methods Programs Biomed.*, vol. 80, no. 3, pp. 187–194, 2005.

[16] V. Srinivasan, C. Eswaran, and N. Sriraam, "Approximate entropy-based epileptic EEG detection using artificial neural networks," *IEEE Trans. Inf. Technol. Biomed.*, vol. 11, no. 3, pp. 288–295, May 2007.

[17] V. N. Vapnik, "An overview of statistical learning theory," *IEEE Trans. Neural Networks*, vol. 10, no. 5, pp. 988–999, Sep. 1999.

[18] M. Zavar, S. Rahati, M.-R. Akbarzadeh-T, and H. Ghasemifard, "Evolutionary model selection in a wavelet-based support vector machine for automated seizure detection," *Expert Syst. Appl.*, vol. 38, pp. 10751–10758, Sep. 2011.

[19] A. B. Gardner, A. M. Krieger, G. Vachtsevanos, and B. Litt, "One-class novelty detection for seizure analysis from intracranial EEG," *J. Mach. Learn. Res.*, vol. 7, pp. 1025–1044, 2006.

[20] S. Katagiri and S. Abe, "Incremental training of support vector machines using hyperspheres," *Pattern Recognit. Lett.*, vol. 27, no. 13, pp. 1495–1507, 2006.

[21] Freiburg Seizure Prediction Project. Freiburg, Germany, 2008 [Online]. Available: http://epilepsy.uni-freiburg.de/freiburg-seizure-prediction-project/eeg-database

[22] M. K. Kiymik, I. Güler, A. Dizibüyük, and M. Akin, "Comparison of STFT and wavelet transform methods in determining epileptic seizure activity in EEG signals for real-time application," *Comput. Biol. Med.*, vol. 35, pp. 603–616, 2005.

[23] T. Kalayci and O. Ozdamar, "Wavelet preprocessing for automated neural network detection of EEG spikes," *IEEE Eng. Med. Biol. Mag.*, vol. 14, no. 2, pp. 160–166, Mar./Apr. 1995.

[24] M. E. Saab and J. Gotman, "A system to detect the onset of epileptic seizures in scalp EEG," *Clin. Neurophysiol.*, vol. 116, no. 2, pp. 427–442, 2005.

[25] S. Grewal and J. Gotman, "An automatic warning system for epileptic seizures recorded on intracerebral EEGs," *Clin. Neurophysiol.*, vol. 116, no. 10, pp. 2460–2472, 2005.

[26] J. Gotman, "Automatic recognition of epileptic seizures in the EEG," *Electroencephalogr. Clin. Neurophysiol.*, vol. 54, pp. 530–540, 1982.

[27] E. D. Übeyli, "Least squares support vector machine employing model-based methods coefficients for analysis of EEG signals," *Expert Syst. Appl.*, vol. 37, no. 1, pp. 233–239, 2010.

[28] C. J. C. Burges, "A tutorial on support vector machines for pattern recognition," *Data Mining Knowledge Discovery*, vol. 2, pp. 121–167, 1998.

[29] A. Temko, E. Thomas, W. Marnane, G. Lightbody, and G. Boylan, "EEG-based neonatal seizure detection with support vector machines," *Clin. Neurophysiol.*, vol. 122, no. 3, pp. 464–473, 2011.

[30] Z. Huang and M. P. Harper, "Speech activity detection on multichannels of meeting recordings," *Lecture Notes in Computer Science*, vol. 3869, pp. 415–427, 2006.

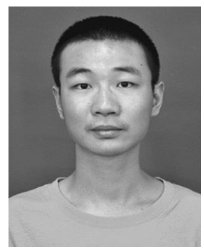
[31] K. K. Majumdar and P. Vardhan, “Automatic seizure detection in ECoG by differential operator and windowed variance,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 19, no. 4, pp. 356–365, Aug. 2011.
[32] A. Aarabi, R. Fazel-Rezai, and Y. Aghakhani, “A fuzzy rule-based system for epileptic seizure detection in intracranial EEG,” *Clin. Neurophysiol.*, vol. 120, pp. 1648–1657, 2009.
[33] E. C.-P. Chua, K. Patel, M. Fitzsimons, and C. J. Bleakley, “Improved patient specific seizure detection during pre-surgical evaluation,” *Clin. Neurophysiol.*, vol. 122, pp. 672–679, 2011.
[34] S. Raghunathan, A. Jaitli, and P. P. Irazoqui, “Multistage seizure detection techniques optimized for low-power hardware platforms,” *Epilepsy Behav.*, vol. 22, pp. S61–S68, 2011.
[35] P. Zarjam and M. Mesbah, “Discrete wavelet transform based seizure detection in newborns EEG signals,” in *Proc. 7th Int. Symp. Signal Process. Appl.*, 2003, vol. 2, pp. 459–462.
[36] S. Mihandoost, M. C. Amirani, and B. Z. Varghahan, “Seizure detection using wavelet transform and a new statistical feature,” in *Proc. 2011 5th Int. Conf. Appl. Inf. Commun. Technol.*, 2011, pp. 1–5.
[37] H. Y. Chang, S. C. Yang, S. H. Lan, and P. C. Chung, “Epileptic seizure detection in grouped multi-channel EEG signal using ICA and wavelet transform,” in *Proc. 2010 IEEE Int. Symp. Circuits Syst.*, 2010, pp. 1388–1391.

Yinxia Liu received the B.E. degree in electronic information engineering from China West Normal University, Nanchong, China, in 2010. She is currently working toward the M.S. degree in the School of Information Science and Engineering, Shandong University, Jinan, China.

Her research interests include biomedical signal processing and machine learning.

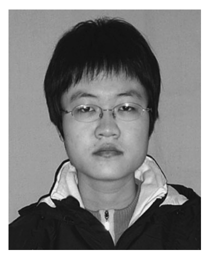
Weidong Zhou received the B.E. degree and M.E. degree from Zhejiang University, Hangzhou, China, in 1986 and 1989, respectively, and received the Ph.D. degree from Shandong University, Jinan, China, in 2005.

He is currently a Professor in the School of Information Science and Engineering at Shandong University. He has published more than 60 articles in academic journals and conference papers. His research interests include biomedical signal and image processing, intelligent information processing.



Qi Yuan received the B.E. degree from Tianjin University of Technology and Education, Tianjin, China, in 2009. He is currently working toward the M.S. degree and Ph.D. degree in the School of Information Science and Engineering, Shandong University, Jinan, China.

His research interests include biomedical signal processing and pattern recognition.



Shuangshuang Chen received the B.E. degree from Qingdao University of Science and Technology, Qingdao, China, in 2010. She is currently working toward the M.S. degree in the School of Information Science and Engineering at Shandong University, Jinan, China.

Her research interests include information processing and pattern recognition.