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Clin EEG Neurosci 2013 44: 247 originally published online 22 April 2013
DOI: 10.1177/1550059413483451

The online version of this article can be found at:
http://eeg.sagepub.com/content/44/4/247

Published by:
SAGE
http://www.sagepublications.com

On behalf of:

EEG and Clinical Neuroscience Society

Clinical EEG and Neuroscience
44(4) 247-256

DOI: 10.1177/1550059413483451
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High-Performance Seizure Detection System Using a Wavelet-Approximate Entropy-fSVM Cascade With Clinical Validation

Chia-Ping Shen[1], Chih-Chuan Chen[2], Sheau -Ling Hsieh[3], Wei-Hsin Chen[1], Jia-Ming Chen[3], Chih-Min Chen[1], Feipei Lai[1,4], and Ming-Jang Chiu[1,2,5,6]

Abstract

The classification of electroencephalography (EEG) signals is one of the most important methods for seizure detection. However, verification of an atypical epileptic seizure often can only be done through long-term EEG monitoring for 24 hours or longer. Hence, automatic EEG signal analysis for clinical screening is necessary for the diagnosis of epilepsy. We propose an EEG analysis system of seizure detection, based on a cascade of wavelet-approximate entropy for feature selection, Fisher scores for adaptive feature selection, and support vector machine for feature classification. Performance of the system was tested on open source data, and the overall accuracy reached 99.97%. We further tested the performance of the system on clinical EEG obtained from a clinical EEG laboratory and bedside EEG recordings. The results showed an overall accuracy of 98.73% for routine EEG, and 94.32% for bedside EEG, which verified the high performance and usefulness of such a cascade system for seizure detection. Also, the prediction model, trained by routine EEG, can be successfully generalized to bedside EEG of independent patients.

Keywords

approximate entropy, epilepsy, support vector machine, electroencephalogram

Received November 1, 2012; accepted February 26, 2013.

Introduction

EEG records cerebral electrical activity and detects events of epileptic seizures. Epilepsy is among the most common serious neurological disorders of the brain.[1] The mean prevalence rates in the United States and Europe are 0.52% and 0.68%, respectively,[2] and even higher in developing countries.[3] Routine EEG, which shows temporal and spatial information of the brain's electrical voltages, is often used to monitor activities of the brain.[4] In addition to epileptic seizures, EEG analysis system should be able to detect interictal activities. Previous studies showed that EEG has high sensitivity and specificity for the diagnosis of epilepsy.[5] For example, the 3-Hz spike-and-wave in EEG is unique to petit mal, which is a particular form of absence seizure of childhood. Therefore, spike detection of EEG is important for health professionals.

Various approaches providing automatic seizure detection have been proposed. Weng and Khorasani used amplitude, duration, and coefficients of variation and frequency as inputs for a neural network.[6] Güler and Übeyli proposed a method for seizure detection based on wavelet coefficients, eigenvectors, and support vector machine (SVM).[7–9] The system proposed by Srinivasan et al adopted approximate entropy (ApEn) as the feature classification for seizure detection.[10] Recently, Adeli et al performed a principal component analysis on enhanced cosine radial basis function neural network (RBFNN) to detect seizures,[11] and Tzallas et al demonstrated the suitability of time–frequency analysis to classify EEG segments for epileptic

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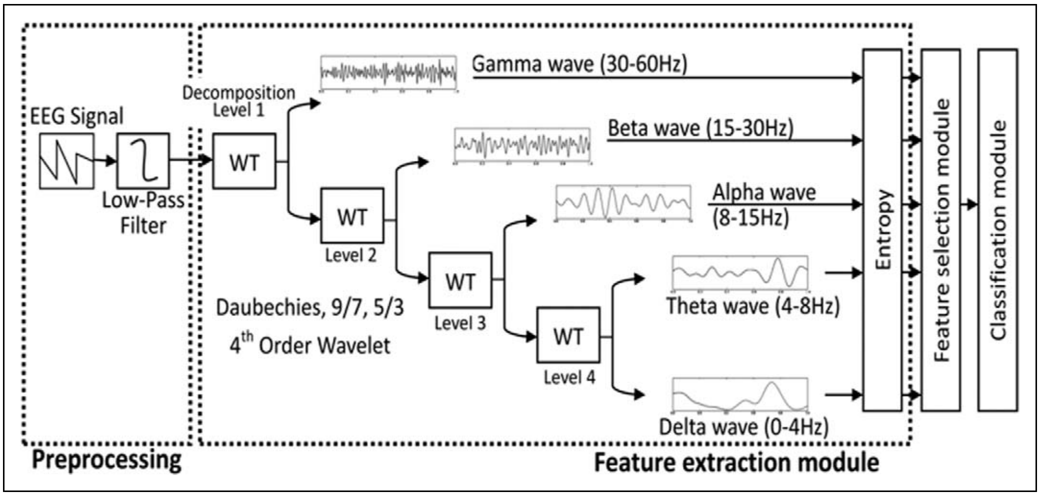

Figure 1. Shows the system architecture, in which the feature extraction module is composed of wavelet transformation and approximate entropy, the feature selection module is composed of Fisher score, and the classification module is composed of any one of support vector machine, *k*-nearest neighbors, or artificial neural network.

seizures.[12] Furthermore, some experts used specific interictal spike patterns as features of neuronal circuits in the hippocampus in terms of cell and network.[13] Although promising results have been reported in these studies, the accuracy of recognition is still low, and the performance of such systems needs to be improved. Furthermore, most of these studies tested performance on open source data but lacked validation with clinical data. To improve accuracy of seizure detection, we propose to construct a comprehensive EEG analysis system, which integrates several of the aforementioned technologies.

Methods

The system architecture is depicted in Figure 1. After EEG is preprocessed, the feature extraction module decomposes the input signal into 5 subbands by wavelet analysis, and then, the evaluated wavelet transform (WT) coefficients are arranged into feature vectors, approximately corresponding to γ, β, α, θ, and δ bands of conventional analog EEG analysis. For each band, 5 statistical parameters, including maximum, minimum, mean, standard deviation (SD), and entropy, are calculated. Then, features are further screened by the feature selection module, which sorts and decides the most important feature among the aforementioned parameters. Finally, the classification module determines hyperplanes among all classes based on selected feature sets.

We compared the results of several existing methods for classification, including SVM, *k*-nearest neighbor (KNN), and RBFNN, to determine which has the best performance in such a cascaded EEG analysis system. We tested performance not only on open source data, but also on clinical data.

Acquisition and Preprocessing of EEG

There are 5 sets of EEG in the open source data that can be downloaded from the Web site.[14] Open source data were randomly chosen either as a training or testing data set. Each data group (A-E) contains 100 single-channel EEG segments of 23.6-seconds. Each EEG segment contains 4096 data points (sampling rate 173.6 Hz). Sets A and B were taken from the scalp EEG of 5 healthy volunteers with eyes open (A) and eyes closed (B). Other data were obtained from the intracranial EEG of 5 patients for presurgical diagnosis. Data set *C* was from the hippocampal formation of the hemisphere, while set *D* was from intracranial recordings from the opposite epileptogenic zones; both sets *C* and *D* contained activity during seizure-free intervals. Set E contained only seizure activity from all the recording sites. EEG was acquired at a sampling rate of 173.61 Hz and a 12-bit analog-to-digital conversion.[15]

We collected clinical data from patients receiving routine EEG examinations or bedside EEG monitoring in the Department of Neurology, National Taiwan University Hospital (NTUH). In total, we included routine EEG data from 22 participants (11 women and 11 men), whose ages ranged from 23 to 86 years. There are 3 classes, namely interictal discharges, seizure activity, and normal activity in the routine clinical EEG data. In the patient group (4 women and 6 men), diagnosed with temporal lobe epilepsy with abnormal focal or regional EEG signals, the mean age was 67.2 years (SD = 16.6). In the control group (7 women and 5 men), referred from the outpatient clinic and with normal EEG, the mean age was 43.6 years (SD = 17.5). These patients usually complained of headache or dizziness, and did not have the diagnosis of epilepsy or seizure disorder. Routine EEG was obtained from the 22 outpatients for about 15 minutes in a clinical EEG laboratory.

In order to explore the potential of the method to work in a real-time environment, we further included 2 inpatients who received bedside EEG recordings. The first patient was a 22-year-old man, who had active seizures on awakening in the morning, hereafter designated “ictal case.” The second was a 22-year-old woman, who had very frequent interictal epileptiform discharges in her previous recordings, hereafter designated as "interictal case." These 2 inpatients received long-term bedside EEG for 64 and 60 hours, respectively. Research was approved by the ethical committee of the NTUH.

EEG was collected from 21-channel scalp Ag–AgCl electrodes according to the 10-20 International System[16], and was digitalized at a sampling rate of 200 Hz and a dynamic range of 12 bits. First, the EEG signal was preprocessed by a low-pass filter with a cutoff frequency of 60 Hz, to reduce computational complexity and to retain important EEG information. Second, the recorded EEG was classified into normal EEG, interictal epileptiform discharges, and ictal activities, then segmented into 2-second epochs. Interictal epileptiform discharges met the following conventional criteria[17]: (1) be paroxysmal; (2) include an abrupt change in polarity occurring over several seconds; (3) the duration of each transient should be less than 200 ms (spikes < 70 ms and sharp waves between 70 and 200 ms); (4) the discharge must have a physiology field. EEG abnormalities in patients with seizure disorders may be categorized as either specific or nonspecific. Specific patterns include spikes, sharp waves, spike-wave complexes, temporal intermittent rhythmic delta activity, and periodic lateralized epileptiform discharges, which are all potentially epileptogenic, and provide diagnostically useful information,[17] while the nonspecific changes, such as generalized or focal slow-wave activity, do not.[18] EEG was sampled from the most prominent channel, frequently involving T3(4), T5(6), F7(8), F3(4), or Fp1(2) sites. The most prominent channel was; either the channel with a phase reversal indicating the source of the epileptogenic focus in a bipolar montage or the channel with the highest amplitude in a monopolar montage. EEG of control patients was sampled from a randomly chosen single channel of the aforementioned electrode sites.

The electrographic onset of a seizure is characterized by a sudden change in frequency and the appearance of a new rhythm. Focal onset of the electrographic seizure may evolve through several phases: (1) focal desynchronization or attenuation of EEG activity ($\leq 10\mu V$); (2) focal, rhythmic, low voltage, fast activity (higher than 13 Hz) discharges; and (3) progressive increase in amplitude with slowing that spreads to a regional anatomic distribution. Focal ictal discharges may be recorded as paroxysmal repetitive spikes, spike-waves (3 or more discharges in sequence), or rhythmic fast or θ activity.[19,20] Since EEG experts may have different opinions on EEG classification, the EEG classifications of interictal and ictal activities were examined by 2 EEG experts (CCC and MJC, coauthors of this report). We performed an interrater reliability test between the 2 experts' ratings. We found that the agreement rate was 82% for interictal epileptiform discharges, and 94% for ictal activities (seizure). We used only those signals with the consensus of both experts for processing.

Feature Extraction

Wavelet Transform. Among all the available signal decomposition tools, the WT, which simultaneously extracts the time and frequency characteristics of a signal, is most suitable for extracting the spike-and-wave features.[21] A WT reduces the original signals into a few parameters, while maintaining major characteristics for differentiating the type of EEG records. In addition, the inherent properties of WT, which were proven as an efficient tool for biomedical signal processing,[22] include good time and frequency location and across-subband similarity.

A key advantage of WT over Fourier transforms, is its higher temporal resolution, containing both the frequency and the location information (location in time). Hence, the discrete WT with Daubechies D4, tap 5/3, and tap 9/7 filter pairs[23], was applied to decompose the signal into high- and low-frequency components using 4 steps. The filtered channel results were stored either in low-pass channels (A1, A2, A3, and A4) or in high-pass channels (D1, D2, D3, and D4). The EEG signal decomposition calculated by Daubechies is shown in Figure 2. These results revealed that the values of the D4 and A4 parts were the most important components for our purpose. Mean, SD, maximum, minimum, and entropy values were extracted from the filtered results of each decomposed band. Therefore, there were in total 75 features extracted for 1 EEG segment.

Approximate Entropy

ApEn[24] is one of the nonlinear dynamic parameters that measure complexity of the time series. ApEn is a time domain feature that is capable of classifying complex systems. It was widely used in estimating the regularity of biomedical signals, such as the heart rate variability and the pulsatility of endocrine hormone release. ApEn is also applied to extract different kinds of dynamic EEG rhythms.[25] The calculation of ApEn in equations 1 to 3 with a signal **S** (finite length N) was performed by following step 1 through step 6. The parameter m was the length of the sampling window, which was the dimension of the vector to be shifted, and r was the value of the threshold representing the noise filter level chosen in the range of 0.1 to 0.9. An ApEn sequence reflected the change in uncertainty with time. Large values implied irregularity of a data sequence, whereas small values implied regularity.

1. $\mathbf{S} = [x(1), x(2), \ldots, x(N)]$ is the vector of data sequence.
2. $\mathbf{x}^*(i)$ is a subsequence of $\mathbf{S}$ such that $\mathbf{x}^*(i) = [x(i), x(i+1), \ldots, x(i+m-1)]$ for $1 \leq i \leq N-m+1$, where m is the length of the scaling window.
3. Let $r = k \times \mathrm{SD}$ for $k = 0.1$ to 0.9, where SD is the standard deviation of **S**.
4. For each $1 \leq \mathbf{x}^*(i), \mathbf{x}^*(j) \leq N-m+1$, $i \neq j$, $d[\ ]$ is the operator of Euclidean distance.

$$C_i^m(r) = \frac{\sum_{\mathbf{j=1}}^{\mathbf{N-m+1}} \mathbf{d}[\mathbf{x}^*(\mathbf{i}), \mathbf{x}^*(\mathbf{j})]}{N-m+1}, \tag{1}$$

where $d[\mathbf{x}^*(i), \mathbf{x}^*(j)] = \begin{cases} 1, \mathbf{x}^*(i) - \mathbf{x}^*(j) \leq r \\ 0, \text{otherwise} \end{cases}$

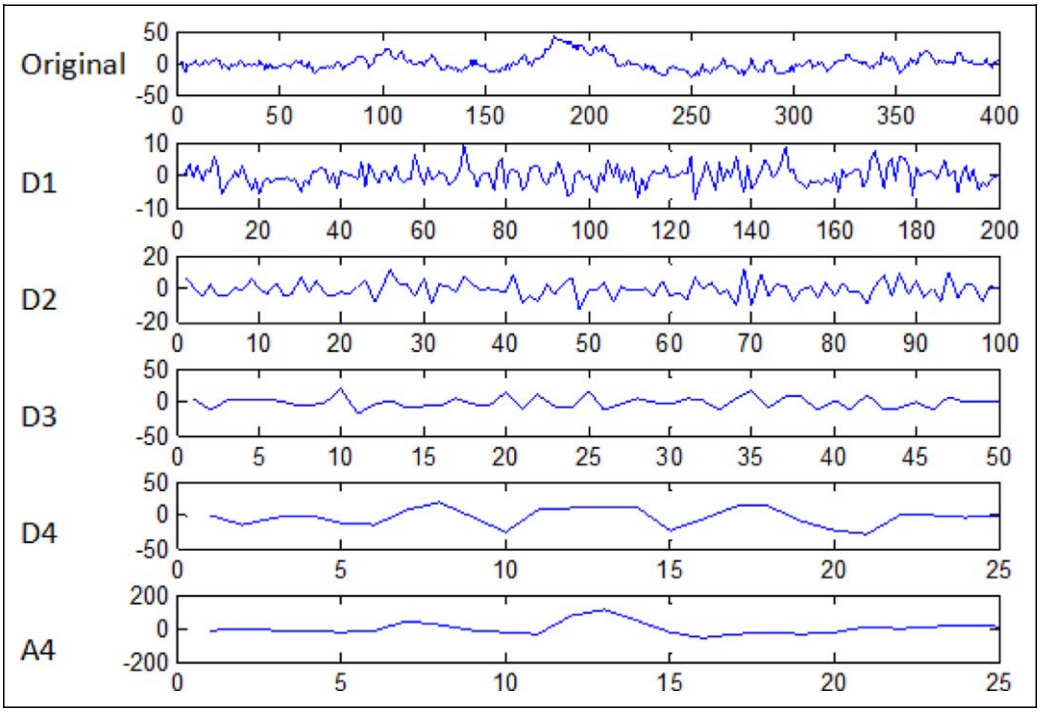

Figure 2. The decomposition results by the Daubechies filter.

5. The quantity $\Phi^m(r)$ is calculated as

$$\Phi^m(r) = \frac{1}{N-m+1}\sum_{i=1}^{N-m+1} \ln C_i^m(r) \tag{2}$$

6. Finally, the ApEn is defined as follows:

$$\text{ApEn} = \Phi^m(r) - \Phi^{m+1}(r) \tag{3}$$

Feature Selection

Fisher score (equation 4) was used to evaluate the importance, $I(a, b, k)$, of a specific feature k, $1 \le k \le m$, for a hyperplane, $\Omega_{a,b}$, corresponding to classes a and b, where $\mu_{a,b}$ denoted the mean value, and $\sigma_{a,b}$ was the SD of the feature k for all training samples.[26] This equation aimed to evaluate the differentiation capability between the 2 classes and the stability in the same class for a given feature, k.

$$I(a,b,k) = \frac{(\mu_{a,k} - \mu_{b,k})^2}{\sigma_{a,k}^2 + \sigma_{b,k}^2} \tag{4}$$

For each hyperplane, the importance of each feature was first calculated then sorted in descending order. The types of selected features were usually varied for different decision hyperplanes. After sorting, the best features were selected and saved.[25]

Classification

Support Vector Machines. SVMs map the input feature vectors into a high-dimensional space to realize the linearity of the classifier.[27] By feeding the algorithm with a data training set, SVM can determine an optimal hyperplane that minimizes the risks.[28] Due to the inherent properties of SVM, it can only determine the hyperplane between 2 different classes; any testing samples must be processed for all combinations between 2 arbitrary classes. Based on this training scheme, the classification problem of 2 different classes is considered. Given a training set of instance-label pairs (x_i, y_i), $1 \le i \le l$, where x_i and y_i denote the input and output domains, respectively, and l denotes the total number of training samples. Thus, w is the weight of training samples, and b is the bias of training samples. In equation 7, C is a parameter of a penalty term chosen by users to design errors, and ξ_i is a slack variable. In addition, the value of C can decide how many errors classifiers can tolerate. Larger C can tolerate more errors to avoid the situation of over fitting, but at low accuracy.

$$\begin{aligned} \min_{w,b,\xi} \quad & \tfrac{1}{2} w^T w + C\sum_{i=1}^{l} \xi_i \\ \text{subject to} \quad & y_i(w^T \boldsymbol{x}_i + b) \ge 1 - \xi_i \\ & \xi_i \ge 0 \end{aligned} \tag{5}$$

All training samples are mapped to a higher dimensional space, ϕ, by the kernel function first. Because the input data were cascaded by the Fisher score in equation 4, the SVM was called fSVM.[29]

k-Nearest Neighbors

KNN is a case-based learning method, which maintains all the training data for decision applications.[30] To imply KNN decision strategy, a metric should be defined for measuring the

Table 1. Results of the Feature Classification on Open Source Data Using Different Methods.

	Sensitivity (%)	Specificity (%)	Accuracy (%)
SVM			
Set A	100	100	99.97
Set B	100	100	
Set C	99.87	100	
Set D	100	99.96	
Set E	100	100	
KNN			
Set A	99.50	99.84	99.10
Set B	99.25	99.93	
Set C	99.87	99.59	
Set D	98.37	99.65	
Set E	98.50	99.84	
RBFNN			
Set A	100	100	99.82
Set B	99.87	100	
Set C	99.75	99.90	
Set D	99.50	99.93	
Set E	100	99.93	

Abbreviations: KNN, *k*-nearest neighbor; RBFNN, radial basis function neural network; SVM, support vector machine.

distance between test data and training samples. One of the most popular choices is Euclidean distance. Then, given a test object, the *k*-closest neighbors are found by comparing the distance metric. Among the *k*-closest data points, the most common class label is then assigned to the test object. An appropriate value should be selected for *K*, because the success of classification is very much dependent on this value.[31] There are several methods to choose the *K* value; one simple idea is to run the algorithm many times with different *K* values ($K =$ 1-10), and choose the one with the best performance.

Artificial Neural Network

The artificial neural network (ANN) is considered a good classifier due to its internal features, such as the adaptive learning ability, robust intelligence, and capability of generalization. It is useful when enough data are available. Hence, ANN plays an important role in the classification of pattern recognition.

The RBFNN[32,33] is employed in this article for the detection of epileptic seizures. In our approach, the diverse features are computed by RBFNN using MATLAB software package. The spread of RBFNN is an important variable for classification. The number of spread is supposed to be in the range of 1 to 500. The best parameters of spread were applied in the experiment.

Performance Evaluation

The performances of classifications are evaluated for 3 parameters, namely, sensitivity, specificity, and accuracy. Each segment of EEG was considered as a sample.

System Implement

The EEG analysis system was implemented on a service-oriented architecture (SOA), using Web service techniques.[34] The design inherits SOA flexibilities, and would provide additional cooperation for further integration and deployment.[35] The Web-based system architecture contains 3 major portions, including the client site, the server site, and the database. All components in the system use the XML format for exchanging messages, and the communication mechanism is based on a simple object access protocol over http handled internally by the .NET environment.[36] The 4 components of the server functionalities include preprocessing, feature extraction, feature selection, and classification.

Results

EEG signals can be considered as a superposition of different frequency bands representing different characteristics. WT provides a useful spectral analysis to decompose several levels within the frequency ranges. An EEG signal was subjected to a 4-level decomposition, which contains the significance of the physiological bands. After processing, the components of the 4 levels were D1, D2, D3, D4, and A4. Based on the WT feature analysis technique, it was not difficult to identify the difference between the normal, interictal, and ictal states (denoted as A, D, and E in the open source data, 3 classes). However, these features were not sufficient to differentiate the complete data set (denoted as A, B, C, D, and E in the open source data, 5 classes).

To consider the measurement of uncertainty, ApEn describes the complexity distribution of the signals. Thus, ApEn combined with WT offered better results than using WT only. The classification accuracy of WT-5 classes, WT-3 classes, WT + ApEn-5 classes, and WT + ApEn-3 classes was 70.17%, 87.52%, 99.97%, and 100%, respectively (all applied fSVM for feature selection). The result showed that WT and ApEn were a good combination for feature extraction. The statistical parameters of 3 kinds of classifiers used for feature selection are reported in Table 1. The overall accuracy of fSVM, KNN, and RBFNN was 99.97%, 99.10%, and 99.82%, respectively (Table 1). The comparison showed that all 3 methods achieve high accuracy of classification, because of the cascaded processing with WT, ApEn, and any 1 of the 3 feature selection methods.

Performance of the fSVM classifier in terms of accuracy can be determined by the penalty *C* (Figure 3).

This plot shows that training model will overfit the data if *C* becomes large. The experimental results indicated that the most important parameter for all hyperplanes was the entropy of D4 (9/7 wavelet), D3 (9/7 wavelet), and D2 (5/3 wavelet). Entropy played an important role in this classification. The other issue for pattern recognition was the length of segmentation, which could be used to predict different window lengths for EEG signals (Table 2). Results showed stable accuracy by a diverse number of signal samples. In other words, it was successful

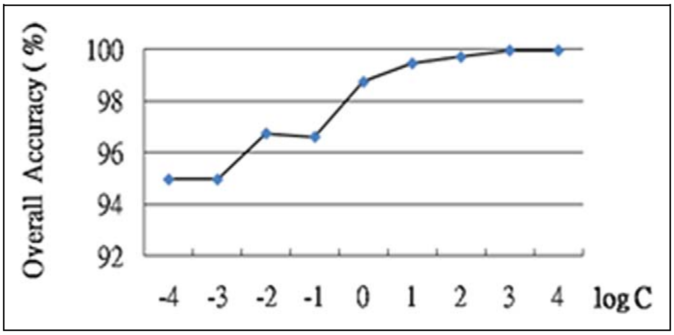

Figure 3. Classification accuracy for different penalty parameter *C*.

Table 2. Accuracy for Different Length of Segmentation With SVM for Open Source Data.

Length	256	512	1024	2048	4096
Accuracy (%)	99.97	99.75	99.8	99.8	100

Abbreviation: SVM, support vector machine.

to extract features using different segmentation lengths of the input data.

To verify the performance of our EEG analysis system, we further tested the system on clinical data with a total number of 712 EEG signals. The 712 EEG signals (1424 seconds) were obtained from a total of 330-minute EEG recordings (around 15 minutes for each participant), by segmenting artifact-free EEG into 2-second epochs. Thus, the training sets were 356, and the testing sets were 356, which were arbitrarily chosen from the total EEG signals. Regarding the problem of the ApEn parameters (m, r), the overall accuracy varied from 94.94% to 97.19%, indicating that the best condition for seizure detection was $m = 3$ and $r = 0.8$ SD (Figure 4). In general, it can be concluded that the overall accuracy remained stable when ApEn was obtained from $m = 2$ to 5. In the example of Figure 5, the distribution was obviously separated by the SD of tap 9/7 (D4), and the maximum values of tap 5/3 (D1), for the normal EEGs and interictal EEGs.

However, this study used only a subset of all features to separate 2 important classes; the average feature number used was only 34.33, whereas the original feature number was 75. These features are composed of ApEn (30%) and the SD (27%), mean (23%), maximum (10%), and minimum (10%) of WT coefficients. The effort of computation was thus significantly decreased by feature selection. In short, ApEn, SD, and mean are better than maximum and minimum. However, maximum and minimum features may also have substantial contribution in classification (Figure 5).

In order to test the stability and practice of the system, we also tested the bedside EEG recordings from the 2 inpatients. Results are summarized below. The EEG of the patient with active seizures, the "ictal case," was about 64 hours long, with 100% sensitivity for seizure detection (13-minute seizure activities out of the total 64-hour recording), and high specificity

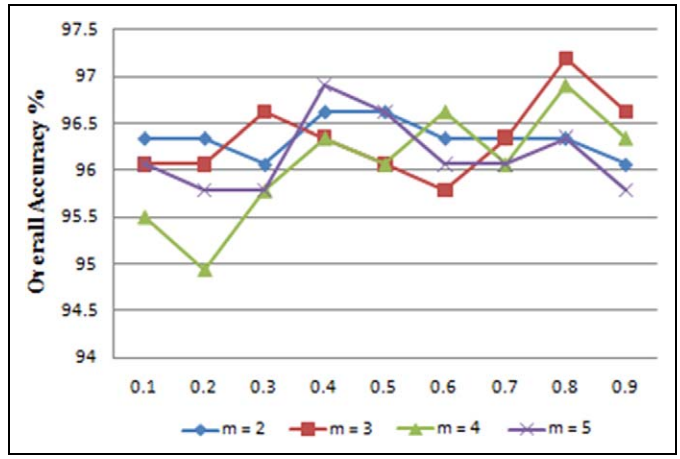

Figure 4. The overall accuracy for different *m* and *r* (x-axis is *r*).

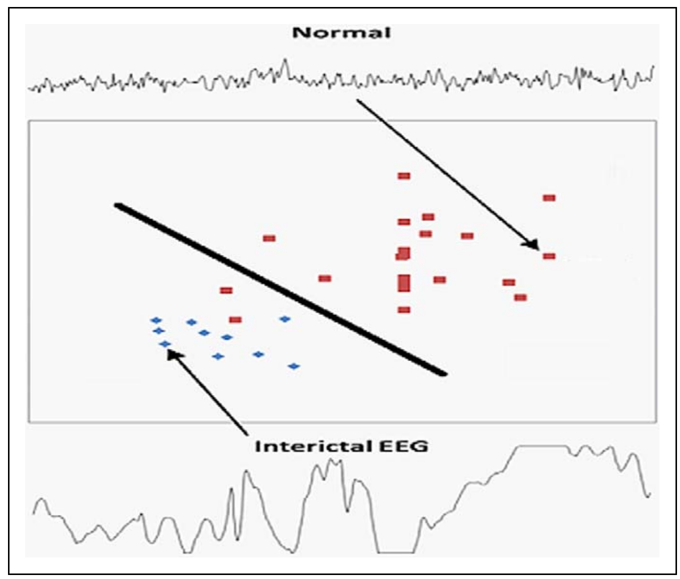

Figure 5. Distribution for normal and interictal EEG with 2 exemplar 2-second EEG segments and their representative positions in the classification hyperplane. EEG indicates electroencephalography.

(97.1%) by SVM. The EEG of the patient with active interictal epileptiform discharges, from the "interictal case", was about 60 hours long, with 81.2% sensitivity for spike detection (accumulated 26 minutes of the total 60 hours recording), and specificity was 91.3% by SVM. The performance on the "interictal case" was similar but worse than on the "ictal case" by SVM classifier. The overall performance of SVM classifier in terms of accuracy on the bedside EEG was 94.32%. The prediction time was very short, taking only 0.23 seconds to predict a 2-second EEG segment. This suggests a high potential of the system to work in real time for its high speed.

The results of the bedside EEG are very similar to the results of our short-duration routine clinical EEG. Performance of seizure detection on bedside EEG is comparable to that of the short-duration EEG. This is because seizure events have a distinct temporal character and are much easier for the system to

Table 3. Comparison of the Performance of Different Studies on the Open Source Data.

	Method	Accuracy (%)
Güler and Übeyli[7]	Wavelet + neurofuzzy	98.68[a]
Übeyli and Güler[9]	Eigenvector + expert model	98.60[a]
Tzallas et al[12]	Time frequency + ANN	89.00[b]
Our study	Wavelet + ApEn + SVM	99.97[c]
Our study	Wavelet + ApEn + RBFNN	99.10[d]
Our study	Wavelet + ApEn + KNN	99.72

Abbreviations: ANN, artificial neural network; ApEn, approximate entropy; KNN, *k*-nearest neighbor; RBFNN, radial basis function neural network; SVM, support vector machine.
[a] $P < .05$.
[b] $P < .001$.
[c] ANOVA was used to compare the performance of different methods by our group or by other groups.
[d] $P < .01$.

Table 4. Comparison of the Performance of Different Studies on the Clinical Data.

	Sensitivity (%)	Specificity (%)
Chaovalitwongse et al[31]	81.29	72.86
Aarabi et al[39]	74	70.1
Acir et al[41]	89.1	85.9
Our study (fSVM)	98.37	100
Our study (RBFNN)	88.61	100
Our study (KNN)	95.12	100

Abbreviations: fSVM, Fisher support vector machine; KNN, *k*-nearest neighbor; RBFNN, radial basis function neural network.

identify. but performance on bedside EEG is much lower for interictal epileptiform discharges, due to increased interference from motion artifacts, and environmental electromagnetic noise in such a bedside condition.

Discussion

To improve on the diagnosis of epilepsy, in addition to clinical information, epileptologists and neurologists depend on laboratory tools, including EEG, magnetic resonance imaging, single-photon emission computed tomography, positron emission tomography, and magnetoencephalography. Among these methods, EEG is the most inexpensive and the most accessible.[37] Some advantages of EEG are low cost, good examination speed, high time resolution, and noninvasiveness.[38–41]

We used WT and ApEn for feature extraction. WT provides a useful spectral analysis to decompose several levels within the frequency domain, and at the same time preserved the time domain features. An EEG signal was subjected to a 4-level decomposition, which contains the significance of the physiological bands. In addition, ApEn is one of the nonlinear dynamic parameters that measure complexity of the time series. WT and ApEn play an important role in features extraction from both frequency and time domains.

Table 3 presents a comparison of the performance between our study and others on the open source data, which shows that our system has the best performance (more than 99%).

Our system performs best, compared to previous studies (Table 4). Sensitivity and specificity of fSVM is better than both KNN ($k = 3$) and RBFNN (spread = 201). The performance of all 3 methods was optimized by tuning their individual best parameters, in which K is from 1 to 10, and spread is between 1 and 500.

Receiver–operating characteristics (ROC) analysis showed that it is much easier to differentiate between normal and epileptic seizure activities, than to differentiate between interictal (epileptiform discharges) and ictal (seizure) activities (Figure 6). One typically difficult case is demonstrated in Figure 7D, which shows a condition where the experts considered the seizure had already begun, but the instrument still classified the segment as interictal activity. This is probably because the program takes a stepwise 2-second epoch for classification. The difficult case is an example of misclassification of ictal EEG into interictal EEG when the epileptiform discharges are evolving.

From the above discussion, we propose that high performance of our system is basically a consequence of the cascade of WT and ApEn. Performance using clinical data is a little bit lower than the open source data, because all the clinical data were obtained from surface recordings with all possible extracranial artifacts. Nevertheless, our approach provides a stable performance for clinical seizure detection, especially with the fSVM feature selection (Table 4).

Area under the curve analysis showed that the area under the ROC curve of SVM is larger than KNN and ANN in Figure 6. In the case of normal versus seizure (RBFNN: 0.906, KNN: 0.972, and SVM: 0.987), or in the case of interictal versus seizure (RBFNN: 0.885, KNN: 0.855, and SVM: 0.914), the performance of SVM is better than KNN and ANN. In addition, as shown in Tables 3 (open source data) and 4 (clinical data), accuracy of the SVM is also better than KNN and ANN.

However, our study is not without limitations. The first is that the open source data are from a limited number of healthy participants (n = 5, surface recordings) and patients with epilepsy (n = 5, presurgical intracranial recordings). Therefore, ceiling effects of the classification are inherent in the open source data set, since intracranial EEGs are free of noise and artifacts from extracranial sources. Despite these apparent limitations, these open source data have been used by a number of studies to test their EEG analysis algorithms. This limitation could be solved by further validation using clinical data. However, comparison of performance on clinical data is limited, due to nonavailability of the clinical data used by other groups. In the future, this could be solved by referring to the clinical data we are now using. Currently, we are analyzing and classifying only on single-channel EEG data. Ideally, the automatic seizure detection system could analyze and classify multichannel (eg, 16 to 32-channels) EEG data from prolonged extracranial recordings, which are full of artifacts due to muscle, body movement, eye movement, electrocardiogram, and nonepileptic paroxysmal EEG transients. The problem was partially met by testing our system on long-duration bedside EEG. Finally, in

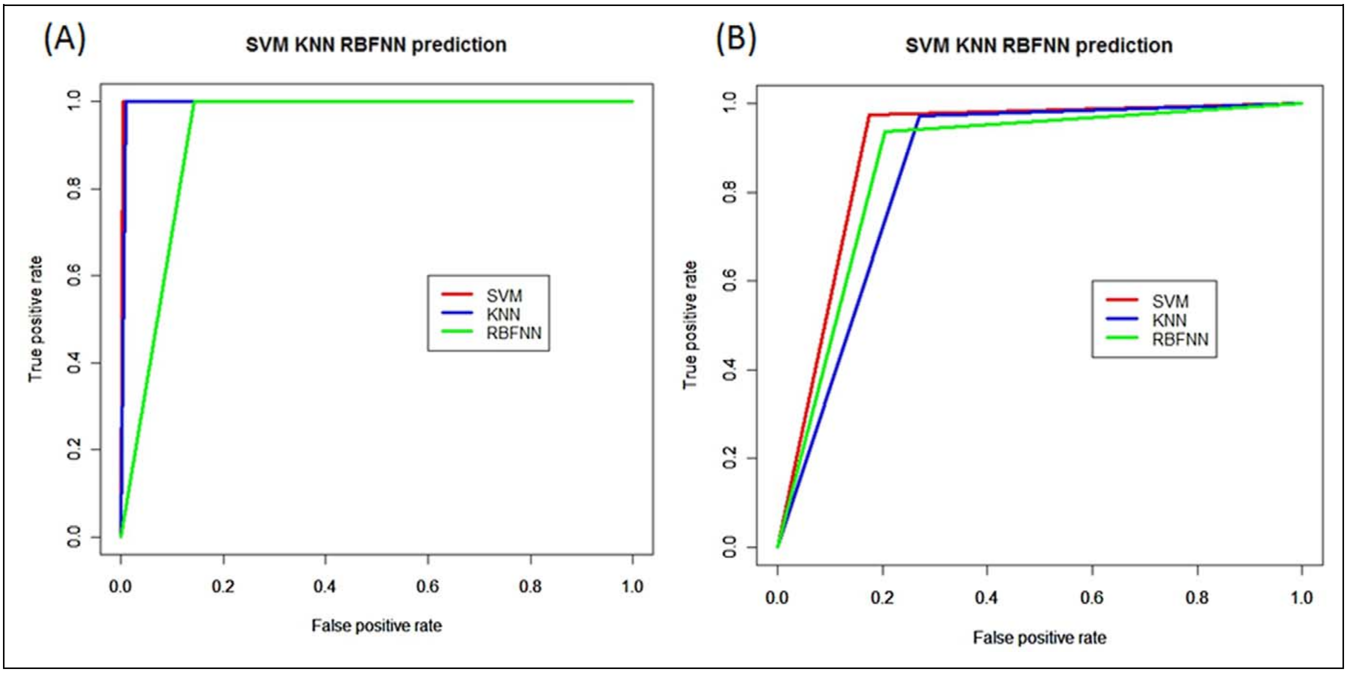

Figure 6. Receiver–operating characteristics curves showing performance of the methods for feature selection. A, Between normal and ictal/interictal activities; (B) between ictal and interictal activities.

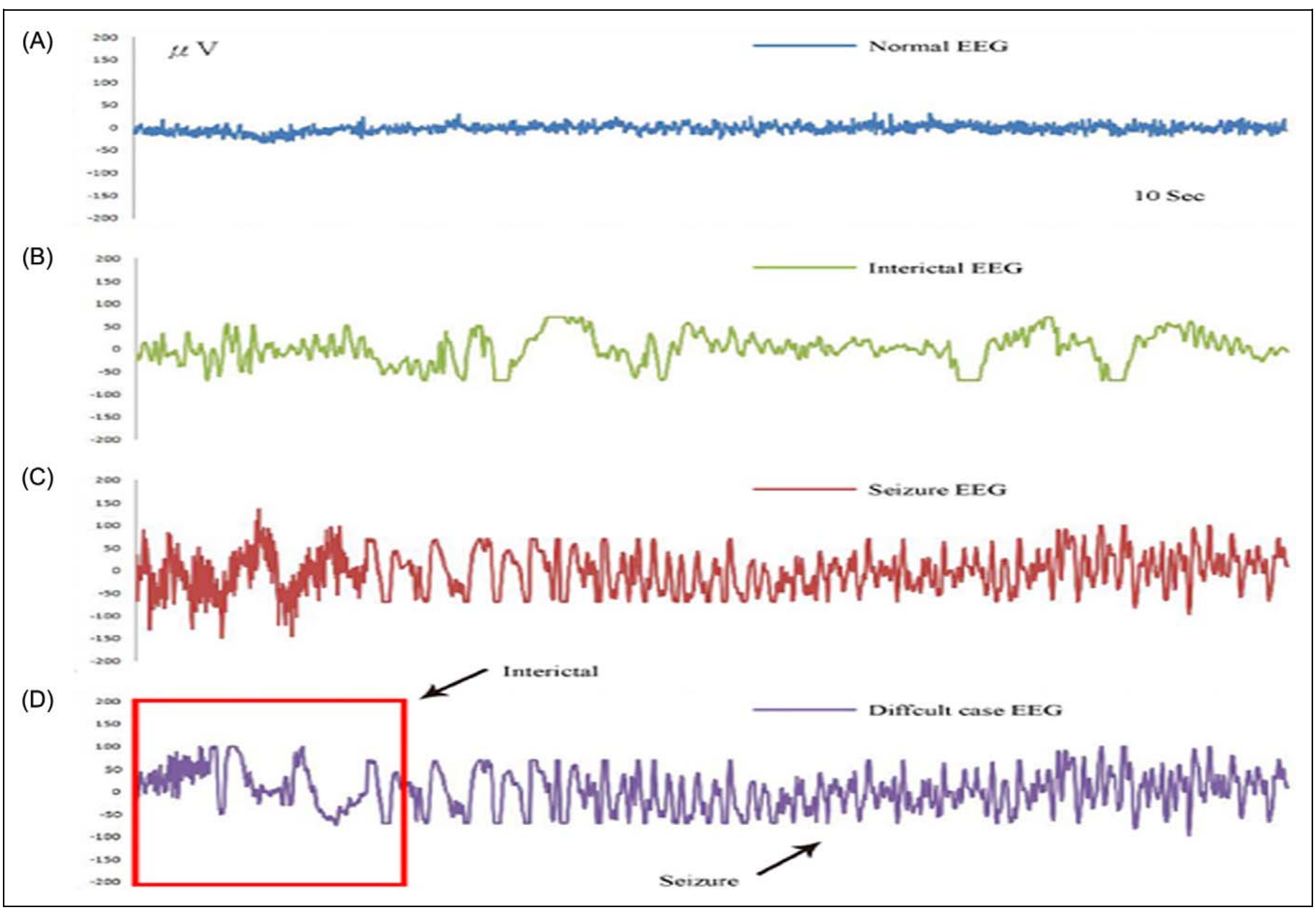

Figure 7. Exemplary electroencephalography of the clinical data. A, normal, (B) interictal, (C) seizure, and (D) evolution from interictal to ictal; in the red rectangle, signal was classified as seizure by experts but as interictal by machine. All displayed in a time frame of 10 seconds.

development of an automatic seizure detection system, we must always remember that the current golden standard for EEG classification is still human visual interpretation, and different EEG readers may have different opinions about a given EEG feature. To tackle this problem, we used only those segments of EEG signal with consensus of the 2 experts, both interictal epileptiform discharges and seizure activities, that contributed to the high sensitivity and specificity of the classification.

Conclusion

We reported a robust and adaptive system based on the hybrid automatic identification system for seizure detection. Currently, interpretation of EEG largely depends on visual analog analysis by neurologists or epileptologists. However, this may be impractical or difficult in some situations, such as analysis of a very long segment data of dozens of hours. An automatic detection system for distinguishing normal, interictal, and ictal activities is of great help in clinical practice. Using the cascaded architecture of WT, ApEn, and feature selection, we can get stable performance, that the accuracy of classification can achieve nearly 100% in the standard open source data, and more than 94% both in routine clinical EEG and in long-duration bedside EEG from the real world. Additional strength of this study, is that the bedside EEG (long term) was predicted by the model trained with routine EEG (short duration). It means that the model trained with routine short-duration EEG can be generalized to analyze EEGs of independent patients, with good performance.

Acknowledgments

The authors thank Prof Chih-Jen Lin and his team for kindly providing the LIBSVM tool.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

References

1. de Boer HM, Mula M, Sander JW. The global burden and stigma of epilepsy. *Epilepsy Behav*. 2008;12(4):540-546.
2. Strzelczyk A, Reese J, Dodel R, Hamer H. Cost of epilepsy: a systematic review. *Pharmacoeconomics*. 2008;26(6):463-476.
3. World Health Organization. *International Classification of Functioning Disability and Health: ICF*. Geneva, Switzerland: WHO; 2001.
4. Fisher RS, van Emde Boas W, Blume W, et al. Epileptic seizures and epilepsy: definitions proposed by the international league against epilepsy (ILAE) and the international bureau for epilepsy (IBE). *Epilepsia*. 2005;46(4):470-472.
5. Cragar DE, Berry DT, Fakhoury TA, Cibula JE, Schmitt FA. A review of diagnostic techniques in the differential diagnosis of epileptic and nonepileptic seizures. *Neuropsychol Rev*. 2002;12(1):31-64.
6. Weng W, Khorasani K. An adaptive structure neural network with application to EEG automatic seizure detection. *Neural Netw*. 1996;9(7):1223-1240.
7. Güler I, Übeyli ED. Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients. *J Neurosci Methods*. 2005;148(2):113-121.
8. Güler I, Übeyli ED. Multiclass support vector machines for EEG signals classification. *IEEE Trans Inf Technol Biomed*. 2007; 11(2):117-126.
9. Übeyli ED, Güler I. Features extracted by eigenvector methods for detecting variability of EEG signals. *Pattern Recogn Lett*. 2007;28(5):592-603.
10. Srinivasan V, Eswaran C, Sriraam N. Approximate entropy-based epileptic EEG detection using artificial neural networks. *IEEE Trans Inf Technol Biomed*. 2007;11(3):512-518.
11. Ghosh-Dastidar S, Adeli H, Dadmehr N. Principle component analysis-enhanced cosine radial basis function neural network for robust epilepsy and seizure detection. *IEEE Trans Biomed Eng*. 2008;55(2 pt 1):512-518.
12. Tzallas AT, Tsipouras MG, Fotiadis DI. Epileptic seizure detection in EEGs using time frequency analysis. *IEEE Trans Inf Technol Biomed*. 2009;13(5):703-710.
13. Demont-Guignard S, Benquet P, Gerber U, Wendling F. Analysis of intracerebral EEG recordings of epileptic spikes insights from a neural network model. *IEEE Trans Biomed Eng*. 2009;56(12): 2782-2795.
14. EEG time series (2005 November).http://www.meb.uni-bonn.de/epileptologie/science/physik/eegdata.html. (accessed on 16 October, 2011).
15. Andrzejak RG, Lehnertz K, Mormann F, Rieke C, David P, Elger CE. Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: dependence on recording region and brain state. *Phys Rev E Stat Nonlin Soft Matter Phys*. 2001;64(6 pt 1):061907.
16. Niedermeyer E, da Silva FL. *Electroencephalography: Basic Principles, Clinical Applications, and Related Fields*. Philadelphia, PA: Lippincott Williams & Wilkins; 2004:140
17. Pedley TA. Interictal epileptiform discharges: discriminating characteristics and clinical correlations. *Am J EEG Technol*. 1980;20:101-119.
18. Zivin L, Ajmone-Marsan C. Incidence and prognostic significance of epileptiform activity in the EEG of non-epileptic subjects. *Brain*. 1969;91(4):751-778.
19. Chiu MJ, Lin CW, Chen CC, et al. Impaired gist memory in patients with temporal lobe epilepsy and hippocampal sclerosis. *Eiplepsia*. 2010;51(6):1036-1042.
20. Foldvary N, Klem G, Hammel J, Bingaman W, Najm I, Lüders H. The localizing value of ictal EEG in focal epilepsy. *Neurology*. 2001;57(11):2022-2028.
21. Daubechies I. The wavelet transform, time-frequency localization and signal analysis. *IEEE Trans Inf Theory*. 1990;36(5):961-1005.
22. Mallat S. A theory for multiresolution signal decomposition: the wavelet presentation. *IEEE Trans Intell*. 1989;11(7):674-693.

23. Cohen A, Daubechies I, Feauveau J. Bi-othogonal bases of compactly supported wavelets. *IEEE Trans Commun Pure Appl Math*. 1992;45(5):485-560.
24. Pincus SM. Approximate entropy as a measure of system complexity. *Proc Natl Acad Sci USA*. 1991;88(6):2297-2301.
25. Chen L, Luo W, Deng Y, Wang Z, Zeng S. Characterizing the complexity of spontaneous electrical signals in cultures neuronal networks using approximate entropy. *IEEE Trans Inf Technol Biomed*. 2009;13(3):405-410.
26. Kao WC, Wei CC. Phonocardiograph signal analysis for detecting heart valve disorders. *Expert Syst Appl*. 2011;38(6):6458-6469.
27. Cortes C, Vapnik V. Support-vector network. *Mach Learn*. 1995; 20(3):273-297.
28. Chen PH, Fan RE, Lin CJ. A study on SMO-type decomposition methods for support vector machines. *IEEE Trans Neural Netw*. 2005;17(4):893-908.
29. Chang CC, Lin CJ. LIBSVM: a library for support vector machines. *ACM Trans Intell Syst Technol*. 2011;2(3):1-27. http://www.csie.ntu.edu.tw/~cjlin/libsvm/. (accessed on 16 October, 2011).
30. Lee Y. Handwritten digit recognition using k-nearest neighbor, radial basis function, and back-propagation neural network. *IEEE Trans Neural Comput*. 1999;3:521-537.
31. Chaovalitwongse WA, Fan YJ, Sachedo RC. On the time series k-nearest neighbor classification of abnormal brain activity. *IEEE Trans Syst Man Cybern*. 2007;37(6):1005-1016.
32. Adeli H, Karim A. A Fuzzy-wavelet RBFNN model for freeay incident detection. *J Transportation Eng*. 2000;126(6):464-471.
33. Karim A, Adeli H. Radial basis function neural network for work zone capacity and queue estimation. *J Transportation Eng*. 2003; 129(5):494-503.
34. Eric N, Greg L. *Understanding SOA with Web Services*. Reading, MA: Addison Wesley; 2005.
35. Bell M. *Introduction to Service-Oriented Modeling.* Service-Oriented Modeling: Service Analysis, Design, and Architecture. Hoboken, NJ: Wiley & Sons; 2008:3.
36. Hsieh SH, Hsieh SL, Chien YH, et al. A newborn screening system based on the service-oriented architecture. *J Med Syst*. 2010;34(4):519-530
37. Teplan M. Fundamentals of EEG measurement. *Meas Sci Rev*. 2002;2(sect 2):1-11.
38. Nandan M, Talathi SS, Myers S, Ditto WL, Khargonekar PP, Carney PR. Support vector machines for seizure detection in an animal model of chronic epilepsy. *J Neural Eng*. 2010;7(3):036001.
39. Aarabi A, Grebe R, Wallois F. A multistage knowledge-based system for EEG seizure detection in newborn infants. Clin Neuropsychol. 2007;118(12):2781-2797.
40. Faul S, Greorcic G, Boylan G, Marnane W, Lightbody G, Connolly S. Gaussian process modeling of EEG for the detection of neonatal seizures. *IEEE Trans Biomed Eng*. 2007;54(12): 2151-2162.
41. Acir N, Oztura I, Kuntalp M, Baklan B, Guzelis C. Automatic detection of epileptiform events in EEG by a three stage based on artificial neural networks. *IEEE Trans Biomed Eng*. 2007; 52(1):30-40.