Classification of the Epileptic EEGs Using the Wavelet-Based Scale Variance Feature

Suparerk Janjarasjitt, Member

ABSTRACT

The detection and classification of epileptic seizures are an important component for the analysis and diagnosis of epilepsy. In this study, the wavelet transform is used as a primary computational tool for extracting characteristics of the epileptic EEG signals at various scales (resolutions). The wavelet-based scale variance defined as log-variance of wavelet coefficients of the epileptic EEG signal is used as a feature vector for the classification. The k-means clustering is then used to classify the epileptic EEG data from the corresponding wavelet-based scale variance features. The computational results show that the excellent classifications between the epileptic EEG data during seizure activity and non-seizure period can be achieved.

Keywords: Electroencephalogram; Epilepsy; Seizure; Wavelet transform; k-means clustering

1. INTRODUCTION

Epilepsy is a common brain disorder in which clusters of neurons signal abnormally [1]. More than 50 million individuals worldwide, about 1% of the world's population are affected by epilepsy [2]. In epilepsy, the normal pattern of neuronal activity becomes disturbed, causing strange sensations, emotions, and behavior, or sometimes convulsions, muscle spasms, and loss of consciousness [1]. There are many possible causes of epilepsy. Anything that disturbs the normal pattern of neuron activity ranging from illness to brain damage to abnormal brain development can lead to seizures [1]. Epileptic seizures are manifestations of epilepsy [3].

Electroencephalogram (EEG) which provides insight information representing the brain's electrical activity is the most utilized signal to assess and detect abnormalities in the electrical activity of the brain, and is a crucial component for the diagnosis of epilepsy [1]. Even though the brain's electrical activity and the unusual pattern of EEG during the epileptic seizure may differ significantly from the brain's electrical activity during non-seizure period, the detection of epileptic seizures is however challenging for a number of reasons.

There have been several techniques, derived from a variety of concepts and theories such as linear analysis, nonlinear analysis and chaos, and artificial neural networks, proposed and used for the detection and classification of epileptic seizures. Spectral analysis is the simplest technique used to examine the characteristics of the EEG signal in frequency and time-frequency domains [3]. The frequency contents of the EEG signal change before and during seizures. Nonlinear analysis techniques such as correlation dimension and Lyapunov exponent have been widely used in EEG analysis including seizure detection [4–6]. Further, most of seizure prediction methods employ nonlinear analysis techniques [3]. In general, the complexity of the dynamics of the neuronal system of the brain is lost during seizures.

Recently, artificial neural networks techniques have played a significant role in classification and pattern recognition including the detection and classification of epileptic seizures [7]. Wavelet is a powerful and efficient computational tool for time-scale analysis which has been applied to various applications. For the seizure detection and classification, wavelet is used as an ideal bandpass filter [8] and also used to extract the features and characteristics of the epileptic EEG signals at different scales or resolutions [3].

In this study, the epileptic EEG signals obtained from different physiological and pathological brain states, and recorded from different regions of the brain are analyzed and then classified. The wavelet transform is used as a primary computational tool for extracting the characteristics of the epileptic EEG signals at various scales. The wavelet-based scale variance that is defined as log-variance of wavelet coefficients of the EEG signals is used as a feature for the classification of the epileptic EEG data. The k-means clustering that is the unsupervised classification method is used for the classification of the epileptic EEG data.

From the computational experiments, the exceptional performance of the classifications of the epileptic EEG data using the simple k-means clustering of the wavelet-based scale variance features is illustrated. The epileptic EEG data recorded during seizure activity can be classified and separated from the epileptic EEG data recorded during seizure-free interval using the wavelet-based scale variance feature. In addition, the results show that the re-

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Suparerk Janjarasjitt is with the Department of Electrical and Electronic Engineering, Ubon Ratchathani University, Warinchamrab, Ubon Ratchathani 34190 Thailand.
E-mail address: ensupajt@ubu.ac.th

gion of the brain where the epileptic EEG data were recorded, i.e., within the epileptogenic zone and faraway from the seizure origin, has an influence on the classification.

2. BACKGROUND

2.1 Wavelet Transforms

Wavelets have been introduced by Grossmann and Morlet [9] for the representation of a function in $L_2(\mathcal{R})$. The continuous wavelet transform of a function $f \in L_2(\mathcal{R})$ is defined as [10]

$$\begin{aligned} Wf(a,b) &= \langle f, \psi_{a,b} \rangle \\ &= \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t) \psi^* \left(\frac{t-b}{a} \right) dt \end{aligned} \tag{1}$$

where ψ is a fix function called mother wavelet. A family of wavelets, $\psi_{a,b}$, is normalized dilations and translations of the mother wavelet ψ [11, 12]:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi \left(\frac{t-b}{a} \right), \quad a > 0, b \in \mathcal{R}. \tag{2}$$

The mother wavelet ψ is well localized both in time and frequency [13]. For a large scale a, the wavelet $\psi_{a,b}$ becomes a stretched version of the mother wavelet corresponding to low frequency content, while for a small scale a, the wavelet $\psi_{a,b}$ becomes a contracted wavelet corresponding to high frequency content. The continuous wavelet transform is invertible if the mother wavelet ψ satisfies the admissibility condition [14]:

$$C_\psi = \int_{-\infty}^{+\infty} \frac{\| \hat{\psi}(\omega) \|^2}{\|\omega\|^2} d\omega < +\infty \tag{3}$$

where $\hat{\psi}(\omega)$ is the Fourier transform of the mother wavelet. To guarantee that the integral of the condition in (3) is finite, it is required that $\hat{\psi}(0) = 0$ [14]. The function f can then be reconstructed by

$$f(t) = \frac{1}{C_\psi} \int_0^{+\infty} \frac{da}{a^2} \int_{-\infty}^{+\infty} Wf(a,b) \psi_{a,b}(t) db. \tag{4}$$

Of particular interest is the discretization of the dilation and translation parameters, a and b, on a dyadic grid, that is $a = 2^m$ and $b = n2^m$ where $m, n \in Z$. Accordingly, a family of dyadic wavelets is given by [10]

$$\psi_{m,n} = \frac{1}{\sqrt{2}^m} \psi \left(2^{-m} t - n \right). \tag{5}$$

It is possible to construct a collection of dyadic wavelets $\psi_{m,n}$ that is orthonormal, i.e., $\langle \psi_{m,n}, \psi_{k,l} \rangle = \delta_{m,k} \delta_{n,l}$ [10]. Consequently, the discrete wavelet transform of the function f is defined by

$$\begin{aligned} d_{m,n} &= \langle f, \psi_{m,n} \rangle \\ &= \frac{1}{\sqrt{2}^m} \int_{-\infty}^{+\infty} f(t) \psi^* \left(2^{-m} t - n \right) dt \end{aligned} \tag{6}$$

where $d_{m,n}$ are called wavelet coefficients, and $d_{m,n}^2$ represent an estimate of the energy of the function f in the vicinity of $t = 2^m n$. In addition, the wavelets $\psi_{m,n}$ associate to the scale 2^m or the resolution 2^{-m}. From a signal processing point of view, a dyadic orthonormal wavelet is an octave band filter. Therefore, the wavelet transform can be interpreted as a constant-Q filtering with a set of octave-band filters which is followed by sampling at the respective Nyquist frequencies [10]. It is also clear that the details or resolution can be added to the signal by adding higher octave bands [10].

Moreover, the partial sum of wavelet coefficients, i.e., $\sum_{n=-\infty}^{+\infty} d_{m,n} \psi_{m,n} = \sum_{n=-\infty}^{+\infty} \langle f, \psi_{m,n} \rangle \psi_{m,n}$, can be interpreted as the difference between two approximations of f at the resolution 2^{-m+1} and 2^{-m} [14]. Multiresolution approximations compute the approximation of signals at various resolutions 2^{-m} with orthogonal projections on different spaces $\mathbf{V_m} \subset \mathbf{V_{m-1}}$ such that $\mathbf{V_m} \in \mathbf{V_{m-1}}$ where $\mathbf{V_m} \in \mathbf{L_2}(\mathcal{R})$ [14].

2.2 The k-means Clustering Algorithm

Clustering is the unsupervised classification of patterns such as feature vectors into groups (clusters) [15]. The k-means is the simplest and most commonly used clustering algorithm that employs a squared error criterion [16]. The squared error criterion is the most intuitive criterion function in partitional clustering techniques. The squared error criterion tends to work well with isolated and compact clusters [15].

The squared error for a clustering $\mathcal{L}$ of a pattern set $\mathcal{H}$ that contains K clusters is [15]

$$\varepsilon^2 (\mathcal{H}, \mathcal{L}) = \sum_{j=1}^{K} \sum_{i=1}^{n_j} \| \mathbf{x_i^j} - \mathbf{c_j} \|^2 \tag{7}$$

where $\mathbf{x_i^j}$ is the ith patterns belonging to the jth cluster and $\mathbf{c_j}$ is the geometric centroid of the jth cluster. The steps of the squared error clustering method are as follows [15]:

1. Choose an initial partition of the patterns for K clusters.
2. Assign each pattern to the closest cluster center.
3. Compute the new cluster centers as the centroids of the clusters.
4. Repeat steps 2–3 until convergence is achieved, i.e., there is no change of the cluster membership.
5. Combine and split clusters based on some heuristic information.

Similarly, the k-means starts with a random initial partition and keeps reassigning the patterns to clusters based on the similarity between the pattern and the cluster centers until a convergence criterion is met, e.g. there is no reassignment of any pattern from one cluster to another, or the squared error ceases to decrease significantly after some number of iterations [15]. The computational complexity of the k-means algorithm is linear to the number of patterns n, i.e.,

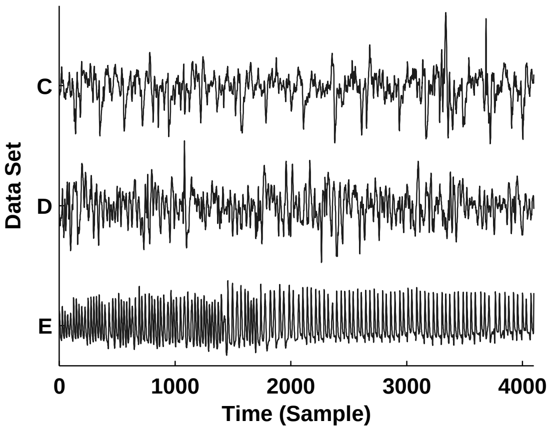


Fig.1: *Examples of EEG time series of the data sets C, D, and E.*

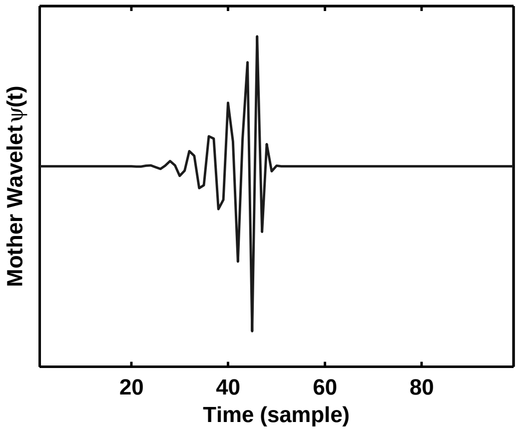


Fig.2: *The mother wavelet of the 25th-order Daubechies wavelet family.*

$O(n)$. A primary disadvantage of the k-means algorithm is that it is sensitive to the selection of the initial partition and may converge to a local minimum of the criterion function value if the initial partition is not properly chosen [15].

The steps of the k-means clustering algorithm are as follows [15]:
1. Initialize K cluster centers by randomly choosing K patterns.
2. Assign each pattern to the closest cluster center.
3. Compute the cluster centers using the current cluster membership.
4. If a convergence criterion is not met, go to step 2.
Typically, the convergence criteria are: no or minimal reassignment of patterns to new cluster centers, or minimal decrease in squared error.

3. METHODS

3.1 EEG Data

There are 3 sets of EEG data, referred to as sets C, D and E, examined in this study. The EEG data are obtained from the Department of Epileptology, University of Bonn (available online at `http://www.epileptologie-bonn.de`) where the EEG data originated from the study presented in [17]. The EEG data were recorded using intercranial electrodes from five epilepsy patients. Further, the EEG data of the set C were recorded from the hippocampal formation of the opposite hemisphere of the brain from where the seizure was thought to have originated. The EEG data of the sets D and E were recorded from within the epileptogenic zone. The EEG data of the sets C and D correspond to EEG data during non-seizure period while the EEG data in the set E were recorded during seizure activity.

Each EEG data set contains 100 epochs of a single-channel EEG signal that were selected to be free of artifacts such as muscle activity and eye movements. The length of each epoch is 4,097 samples (about 23.6s). In addition, the epochs of the EEG signal satisfied the weak stationarity criterion given in [17]. The sampling rate of the EEG data is 173.61 Hz. The bandpass filter of the acquisition system has the spectral bandwidth between 0.50 Hz and 85 Hz [17]. Examples of the EEG signal for each data set are illustrated in Fig. 1.

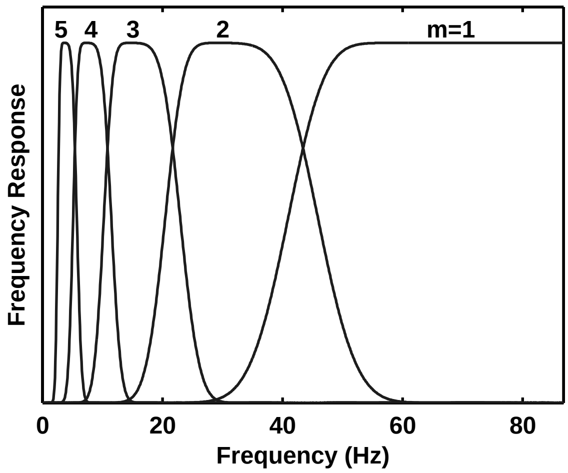


Fig.3: *The associated octave bands of the 25th-order Daubechies wavelets at the scales* $2^1, 2^2, \ldots, 2^5$.

3.2 The Wavelet-Based Scale Variance

The wavelet-based scale variance that is used as the feature vector for the classification of the epileptic EEG signals is composed of 3 steps as follows. First, the wavelet coefficients $d_{m,n}$ of the signal is determined by applying the wavelet decomposition. The variance of the wavelet coefficients of each scale 2^m is then calculated: $v_m = \mathrm{var}\,(d_{m,n})$ for all n. Finally, take log (base 2) of the variance of wavelet coefficients of each scale 2^m. The feature vector of the wavelet-based scale variance of the signal $\mathbf{v}$ can be written

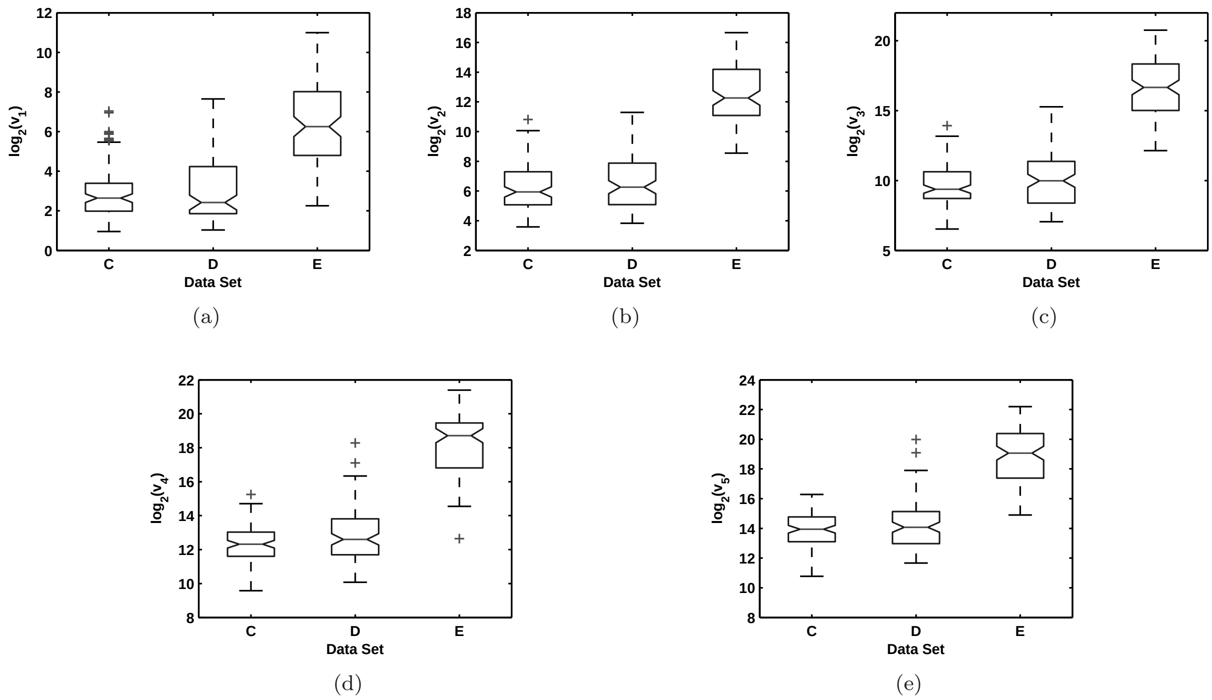


Fig.4: The box plot of the wavelet-based scale variance of the epileptic EEG data of the sets C, D and E at the scale: (a) 2^1, (b) 2^2, (c) 2^3, (d) 2^4 and (e) 2^5.

as

$$\mathbf{v_d} = \begin{bmatrix} \log_2(v_i) \\ \log_2(v_{i+1}) \\ \vdots \\ \log_2(v_j) \end{bmatrix} \tag{8}$$

where the scales $\{2^m;\ m = i, i+1, \ldots, j\}$ are the scale that is used in the classification.

3.3 Analytic Framework

In this study, the 25th-order Daubechies wavelet family is used in the wavelet decomposition where the mother wavelet is illustrated in Fig. 2. The EEG data are decomposed into 5 scales, i.e., $2^1, 2^2, \ldots, 2^5$ which correspond to the levels $m = 1, 2, \ldots, 5$ where the associated octave bands of the 25th-order Daubechies wavelets at the scales $2^1, 2^2, \ldots, 2^5$ are, respectively, 85–43.42, 43.42–21.71, 21.71–10.86, 10.86–5.43 and 5.43–2.72 Hz. Further, the magnitude of the frequency response of the corresponding octave band filters is depicted in Fig. 3. The patterns used for the classification of the epileptic EEG data are the feature vector of the wavelet-based scale variance at only the scales $2^2, 2^3, \ldots, 2^5$ (corresponding to the levels $m = 2, 3, \ldots, 5$) which provide the best outcomes of the classification for these EEG data sets.

In classification, the k-means clustering is employed to classify the feature vectors of the wavelet-based scale variance of the EEG signals. Specifically, the classification of the epileptic EEG signals performed in this study is divided into three tasks as follow:

- Task 1: the classification between the EEG data of the set C and of the set E.
- Task 2: the classification between the EEG data of the set D and of the set E.
- Task 3: the classification between the EEG data of the sets C and D and of the set E.

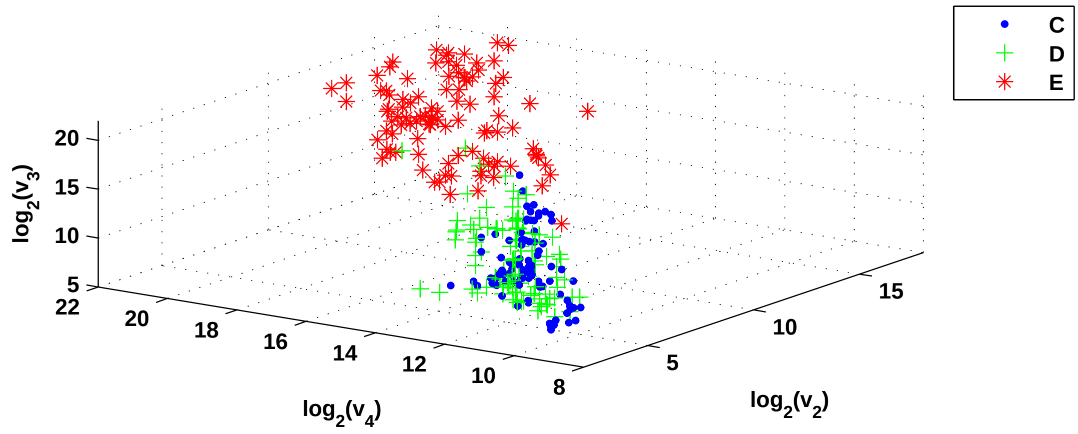
3.4 Evaluation of Performance of the Classification

In addition to the accuracy of the classification of the EEG data, the performance of the classification of the EEG data is evaluated by determining two parameters, i.e., the sensitivity (the true positive ratio) and the specificity (the true negative ratio). The sensitivity and the specificity are given by, respectively,

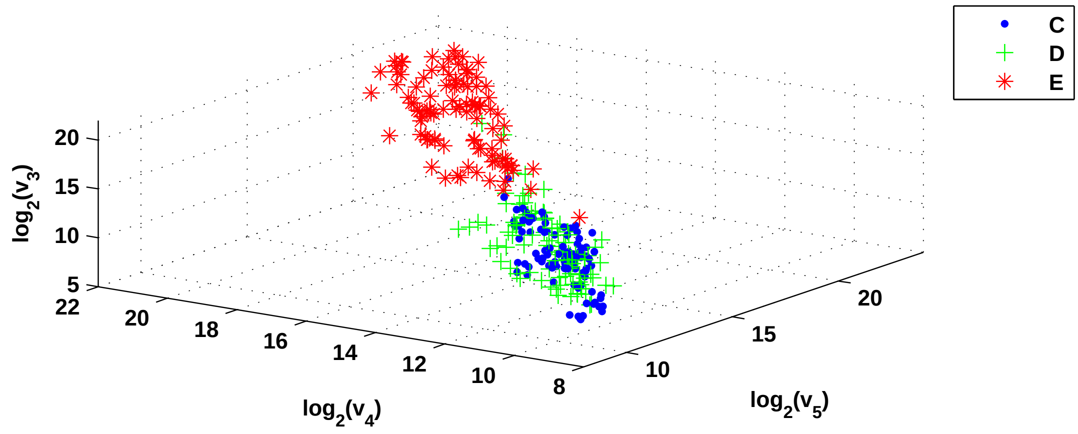
$$S_e = \frac{TP}{TP + FN} \times 100\% \tag{9}$$

$$S_p = \frac{TN}{TN + FP} \times 100\% \tag{10}$$

where TP, FN, TN, and FP denote the number of the true positives, the number of the false negatives, the number of true negative, and the number of the false positives, respectively.



(a)



(b)

Fig.5: *The wavelet-based scale variance of the epileptic EEG data of the sets C, D and E at the scales: (a) 2^2, 2^3 and 2^4 and (b) 2^3, 2^4 and 2^5.*

Table 1: *The Wavelet-Based Scale Variance of the EEG Data*

Scale	Set C	Set D	Set E
2^1	3.0103	3.0077	6.3764
	±1.4025	±1.4430	±2.0805
2^2	6.2433	6.5470	12.4581
	±1.6252	±1.7452	±1.9467
2^3	9.5599	10.0714	16.7245
	±1.5252	±1.8045	±2.0125
2^4	12.2154	12.8257	18.2717
	±1.2330	±1.5669	±1.7967
2^5	13.7775	14.1975	18.8500
	±1.2381	±1.5345	±1.8052

4. RESULTS

4.1 The Wavelet-Based Scale Variance of the Epileptic EEGs

The wavelet-based scale variance features of the EEG data of the sets C, D and E at the scales 2^1, 2^2, 2^3, 2^4 and 2^5 (corresponding to the levels $m = 1, 2, \ldots, 5$) are compared in box plots shown in Fig. 4(a)–Fig. 4(e), respectively. The mean and standard deviation values of the wavelet-based scale variance features of the EEG data of the sets C, D and E at the scales 2^1, 2^2, 2^3, 2^4 and 2^5 are summarized in Table 1. Obviously, the wavelet-based scale variance feature of the EEG data of the set E tends to be higher than that of the EEG data of the set D, and the wavelet-based scale variance feature of the EEG data of the set D tends to be higher than that of the EEG data of the set C. Further, the wavelet-based scale variance feature of the EEG data of the set E is significantly higher than that of the EEG data of the sets C and D with p-value much less than 0.0001 ($p \ll 0.0001$) at all scales $2^1, 2^2, \ldots, 2^5$. There is however not a statistically significant difference between the wavelet-based scale variance features of the EEG data of the sets C and D at all scales $2^1, 2^2, \ldots, 2^5$.

Furthermore, the wavelet-based scale variance features of the EEG data of the sets C, D and E at the

Table 2: *Classification Results of Task 1*

	No. of Correct Classification	No. of False Classification
Set C	99	1
Set E	99	1

Table 3: *Classification Results of Task 2*

	No. of Correct Classification	No. of False Classification
Set D	95	5
Set E	99	1

Table 4: *Classification Results of Task 3*

	No. of Correct Classification	No. of False Classification
Sets C and D	194	6
Set E	99	1

scales 2^2, 2^3, 2^4 and 2^5 (corresponding to the levels $m = 2$, 3, 4 and 5) that are the feature vectors used in the classification of the EEG data are illustrated in 3-D plots. Fig. 5(a) exhibits the formation of the wavelet-based scale variance features of the EEG data of the sets C, D and E at the scales 2^2, 2^3 and 2^4 while Fig. 5(b) exhibits the formation the wavelet-based scale variance features of the EEG data of the sets C, D and E at the scales 2^3, 2^4 and 2^5. It is shown that the wavelet-based scale variance feature of the EEG data of the set E (plotted in the "*" mark) is well-grouped and aligned on one side of the plots, while the wavelet-based scale variance features of the EEG data of the sets C and D (plotted in the "o" and "+" marks, respectively) are mixed together and aligned on the opposite side of the plots. Visually, the wavelet-based scale variance features therefore show a promising result for the classification of the EEG data.

4.2 The Classification of the Epileptic EEGs

The wavelet-based scale variance features of the EEG data of the sets C, D and E at the scales 2^2, 2^3, 2^4 and 2^5 as shown in Fig. 5(a) and Fig. 5(b) are used as the feature vectors for the classification of the epileptic EEG data using k-means clustering. The outcomes of the classification of the epileptic EEG data of Task 1, Task 2, and Task 3 are, respectively, summarized in Table 2, Table 3, and Table 4. The accuracy of the classification of the epileptic EEG data for the set C in Task 1 is 99.00%, while the accuracy of the classification of the epileptic EEG data for the set D in Task 2 is 95.00%. Also, the classification of the epileptic EEG data for the set E is 99.00% accurate in all three tasks, i.e., Task 1, Task 2 and Task 3.

Table 5: *Sensitivity and Specificity of the Classification*

Task	Sensitivity (S_e)	Specificity (S_p)
1	99.00%	99.00%
2	95.19%	98.96%
3	94.29%	99.49%

Accordingly, from the perspective of the epilepsy detection and classification, the sensitivity (S_e) and the specificity (S_p) of Task 1, Task 2, and Task 3 are 99.00% and 99.00%, 95.19% and 98.96%, 94.29% and 99.49%, respectively, as also illustrated in Table 5.

In general, the performance of the classification between the epileptic EEG data in the sets C and E is better than the performance of the classification between the epileptic EEG data in the sets D and E. Therefore, this implies that the feature of the epileptic EEG signals in the set D, the wavelet-based scale variance feature, is different from the feature of the epileptic EEG signals in the set C even though the EEG data of both sets, C and D, correspond to the epileptic EEG data during non-seizure period. Further, the epileptic EEG signals in the set D are slightly more similar to the ones in the set E where the EEG data of both sets, D and E, were recorded from within the epileptogenic zone.

5. DISCUSSION

In this study, the wavelet decomposition is used to extract the characteristics of the epileptic EEG data that are recorded during seizure activity and seizure-free interval, and also obtained from within the epileptogenic zone and faraway from the corresponding seizure origin at various scales or resolutions. The log-variance of wavelet coefficients of the epileptic EEG data is used as the element of the pattern that is used in the classification of the epileptic EEG data. Further, a set of the log-variance of wavelet coefficients of the epileptic EEG data at various scales, the wavelet-based scale variance feature, is used as the pattern for the classification of the epileptic EEG data.

From the computational results, it is shown that there is a significant difference between the wavelet-based scale variance of the epileptic EEG data of the set E which correspond to the EEG data recorded during seizures and of the epileptic EEG data of the sets C and D which correspond to the EEG data during non-seizure period. As a result, the epileptic EEG data during seizure activity can be excellently classified even the unsupervised method, the k-means clustering, is employed for the classification of the epileptic EEG data and there are no prior knowledge and training required. The seizure activity can then be decently detected using the wavelet-based scale variance feature.

The classification results also suggest that the region of the brain where the epileptic EEG data were recorded has an influence on the the analysis and diagnosis of epilepsy because it is shown that the wavelet-based scale variance features of the epileptic EEG data that are obtained from different regions of the brain, i.e., within the epileptogenic zone and faraway from the corresponding seizure origin, are slightly different from each other. Therefore, the position of the EEG data acquisition plays a role in the classification of the epileptic EEG data that can lead to a different performance of the classification.

Furthermore, the wavelet-based scale variance approach is applied to examine the characteristics of the EEG signal of an epilepsy patient that manifests the generalized tonic-clonic seizure [18]. From the study, it is shown that the epileptic EEG signal exhibits different characteristics of the wavelet-based scale variance corresponding to various physiological and pathological states of the brain. The physiological and pathological states of the brain can be characterized using the wavelet-based scale variance [18].

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Suparerk Janjarasjitt received his M.S. in 2002 and Ph.D. in 2006 in Systems and Control Engineering from Case Western Reserve University, Cleveland, OH, U.S.A. He has been a faculty member of the Department of Electrical and Electronic Engineering, Ubonratchathani University, Thailand since he received his B.Eng. (Hons.) in Electrical Engineering in 1998. Also, he currently holds an adjunct assistant professor position at the Department of Electrical Engineering and Computer Sciences, Case Western Reserve University, Cleveland, OH, U.S.A.

His research interests include the development of advanced computational tools and techniques, and the use of complex systems analysis techniques in various applications including biology and medicine, for a deeper understanding of the characteristics and behaviors of underlying biological and physiological systems corresponding to different states or conditions, namely health and disease. His current research projects are supported by various sources of funding including the Thailand Research Fund (TRF), the Commission on Higher Education (CHE), the Ministry of Education, Thailand, the Coordinating Center for Thai Government Science and Technology Scholarship Student (CSTS), the National Science and Technology Developement Agency (NSTDA), and Ubon Ratchathani University.