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Epileptic seizure detection based on imbalanced classification and wavelet packet transform

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ABSTRACT

Purpose: Automatic seizure detection is significant for the diagnosis of epilepsy and the reduction of massive workload for reviewing continuous EEG recordings.
Methods: Compared with the long non-seizure periods, the durations of the seizure events are much shorter in the continuous EEG recordings. So the seizure detection task can be regarded as an imbalanced classification problem. In this paper, a novel method based on the weighted extreme learning machine (ELM) is proposed for seizure detection with imbalanced EEG data distribution. Firstly, the wavelet packet transform is employed to analyze the EEG data and obtain the time and frequency domain features, and the pattern match regularity statistic (PMRS) is used as the nonlinear feature to quantify the complexity of the EEG time series. After that, the EEG feature vectors are discriminated by the weighted ELM. It can assign different weights for the EEG feature samples according to the class distribution, so that to effectively moderate the bias in performance caused by imbalanced class distribution.
Results: The metric G-mean which takes into account of both the sensitivity and specificity is used to evaluate the performance of this method. The G-mean of 93.96%, event-based sensitivity of 97.73% and false alarm rate of 0.37/h are yielded on the publicly available EEG dataset.
Conclusion: The comparison with other detection methods shows the superior performance of this method, which indicates its potential for detecting seizure events in clinical practice. Additionally, much larger amounts of true continuous EEG data will be used to test the proposed method further in the future work.

1. Introduction

Epilepsy is a neurological disorder which is characterized by the recurrence of sudden abnormal reactions of brain [1]. Epileptic seizures resulting from excessive neuronal discharge are usually accompanied by disturbances in terms of movement, sensation, mood, or mental function [2,3]. There are about 37 million patients around the world suffering from this kind of chronic neurological disorder. It is well-known that the electroencephalogram (EEG) is able to record the voltage differences between electrodes placed on the scalp or cerebral cortex. It has closely relationship with physiological and pathological functions of the brain. Hence, EEG plays an important role in the diagnosis of epilepsy and in the evaluation of presurgical epileptogenic zone [4,5]. Massive amounts of data are generated by EEG monitoring systems, and so the visual inspection of long EEG recordings can be very tedious and time-consuming. From this point of view, an automatic seizure detection technology is of great worth in support of the epilepsy diagnosis.

Many kinds of seizure detection techniques have been proposed so far. A widely applicable technique was developed by Gotman [6,7]. EEG signals were divided into half waves, and then the seizure detection was performed by extracting the features of peak amplitude, duration, slope and sharpness. Considering EEG signals which have characteristics of non-stationarity, there were many

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detection approaches employing the wavelet transform technique. For instance, Liu et al. [8] decomposed EEG signals into time-frequency representations using the discrete wavelet transform (DWT). In their approach, the effective features in terms of relative energy and amplitude, coefficient of variation, and fluctuation index were calculated at the selected scales for ictal EEG identification. With the development of nonlinear dynamics theory, various nonlinear features of EEG signals, including approximate entropy [9], largest Lyapunov exponent [10], Hurst exponent [11], lacunarity [12] and fractal dimensions [13] were estimated for detecting seizure activities.

In recent years, there were a number of powerful classification tools, including support vector machine (SVM) [14], decision tree [15], Bayesian linear discriminant analysis (BLDA) [16], quadratic discriminant analysis (QDA) [17], and different types of artificial neural networks [18,19] applied for EEG feature classification. Since a seizure event typically takes less than 300 s [20], which are much shorter than the duration of non-seizure periods in long-term continuous EEG recordings, it is clear that there is an intractable problem of imbalanced class distribution existing in the task of seizure detection, because the classification algorithm has a natural tendency to be strongly biased towards the majority class that the non-seizure data are belonging to.

In this paper, the weighted extreme learning machine (ELM) [21] is introduced to resolve this imbalance problem at the algorithmic level. The original ELM can be implemented fast and has well generalization performance on many classification tasks [22]. By integrating with the weighting scheme, a heavy weight is able to be assigned to the minority class the seizure data belonging to, while the non-seizure data from the majority class can be assigned with a relative light weight. Consequently, the long-term EEG signals with the imbalanced class distribution can be well perceived by the weighted ELM algorithm.

On the other hand, it is well-known that the non-stationarity is a typical nature of EEG signals. Therefore, the wavelet packet transform (WPT) is applied into the EEG signal analysis, since WPT is able to capture the non-stationary information, including frequency variation and magnitude undulation by the mean of the different time windows [23]. And then the features in both time domain and frequency domain, i.e. relative amplitude and integrated power, can be extracted from the component signals yielded by the wavelet packet decomposition (WPD). Furthermore, the pattern match regularity statistics (PMRS) [24] are used to quantify the nonlinear characteristics of the EEG signals as a supplement feature of the WPT.

The performance and effectiveness for the approach proposed by this paper are evaluated using the public available EEG dataset. To take into account of the imbalanced class distribution of the EEG data, an evaluation metric, named G-mean, is employed in this research work [21]. The numerical results demonstrate that the proposed approach has a great potential for clinical application.

2. Materials and methods

2.1. EEG dataset

The EEG data used in this research work are obtained from the Epilepsy Center at the University Hospital of Freiburg, Germany [25]. The whole complete dataset consists of 21 patients suffering from medically intractable focal epilepsy. All the data are recorded before surgery monitoring with invasive electrodes using a Neurofile NT digital video EEG system with 128 channels, at a sampling rate of 256 Hz with a 16-bit A/D converter. Among these patients, three focal and three extra-focal contacts were previously chosen by certified Epileptologists.

For each individual patient, there are two to five hours of EEG data containing seizure activities. The first seizure event for each individual patient is used for training, and the second is used as the validation set for determining the parameters being used in the detection model. The non-seizure EEG data for training purpose are 50 times the length of the seizure data. The remaining seizure events are utilized to evaluate the performance for the proposed approach in this study. Note that patients #8 and #13 are not considered by this study because there are only two seizure events available for each of them, respectively. The descriptions of the EEG data used in this study are summarized in Table 1. Furthermore, more than 20 h of interictal EEG data without seizure events are employed to test the specificity and false alarm rate for each of the 19 patients except patient #8 and #13. Therefore, 501.40 h of EEG data are used for the performance evaluation in this study.

2.2. Analysis using wavelet packet transform

The wavelet packet transform (WPT) is a generalization format of the classical wavelet transform with further decomposition of both the signal approximation and the signal details obtained by

Table 1
Summary of the EEG data used in this study.

Patient	Gender	Seizure Type	Average Seizure Duration (s)	Number of Used Seizures
1	F	SP	13.14	4
2	M	SP,CP,GTC	118.19	3
3	M	SP,CP	92.66	5
4	F	SP,CP,GTC	87.39	5
5	F	SP,CP,GTC	44.88	5
6	F	CP,GTC	66.88	3
7	F	SP,CP,GTC	153.50	3
9	M	CP,GTC	113.69	5
10	M	SP,CP,GTC	492.01	4
11	F	SP,CP,GTC	157.26	4
12	F	SP,CP,GTC	55.06	4
14	F	CP,GTC	216.40	4
15	M	SP,CP,GTC	145.39	4
16	F	SP,CP,GTC	121.04	5
17	M	SP,CP,GTC	86.16	5
18	F	SP,CP	13.69	5
19	F	SP,CP,GTC	12.54	4
20	M	SP,CP,GTC	85.67	5
21	M	SP,CP	83.09	5
Total	–	–	110.05	82

F: Female, M: Male, SP: simple partial seizure, CP: complex partial seizure, and GTC: generalized tonic-clonic seizure.

wavelet transform at each level. Thereby, a time-frequency analysis with higher resolution can be achieved for non-stationary EEG data.

The WPT decomposes the EEG data into a set of wavelet packet nodes in a format of a complete binary tree as shown in Fig. 1. One of the well-known Daubechies wavelets, named DB4, is deployed as the mother wavelet in this research work, since it can effectively detect the changes of EEG data due to its smoothing feature [26]. The EEG signal bandwidth is limited to 128 Hz. According to the work of Grewal and Gotman [27], the most seizure activities are in a frequency range of 3–30 Hz, but it is not uncommon to see the fast rhythmic activities in a frequency range of 40–50 Hz. Hence, the coefficients of the nodes $(3, 0)$, $(3, 1)$, $(3, 2)$ and $(3, 3)$ in Fig. 1 are reconstructed to obtain the corresponding wavelet packet component signals$f_3^0(t)f_3^1(t)$, $f_3^2(t)$, $f_3^3(t)$, respectively.

In order to remove low frequency components, which are unrelated to seizure activities, the WPT is deployed again to further decompose the component signal$f_3^0(t)$to yield a wavelet packet tree at a depth of two. As shown in Fig. 2, the coefficients of node (2, 0) corresponding to the low frequency components are set to a value of zero. Hence, the wavelet packet tree is reconstructed to give back$f'_3 0(t)$as depicted in Fig. 2. Finally, the EEG features in both time domain and frequency domain can be extracted from the component signals$f'_3 0(t)$, $f_3^1(t)$, $f_3^2(t)$, $f_3^3(t)$, respectively.

2.3. Feature extraction

2.3.1. Relative amplitude

In the majority of seizures, the rhythmic seizure component at some points usually has a bigger amplitude than it has in the pre-seizure background [28]. Hence, the relative amplitude is calculated as a ratio of the analyzed EEG epoch over the average amplitude of the background. Note that the background is defined as a period of 240 s of EEG data, which is always ending 120 s prior to the analyzed EEG epoch. This gap of 120 s is selected to allow a gradual onset of a seizure. The reason to set the 240 s is to guarantee a steady estimation for the background [27]. Furthermore, in this research, the relative amplitudes for the selected wavelet packet component signals are used to evaluate the fluctuation of the EEG amplitudes. And the large quantity of relative amplitudes is able to forecast possible seizure activities.

2.3.2. Spectral analysis

The power spectral density (PSD) function describes the distribution of the signal power in frequency domain. Due to excessive discharges of large groups of neurons, the power of the EEG signal increases evidently during a seizure activity. In this case,

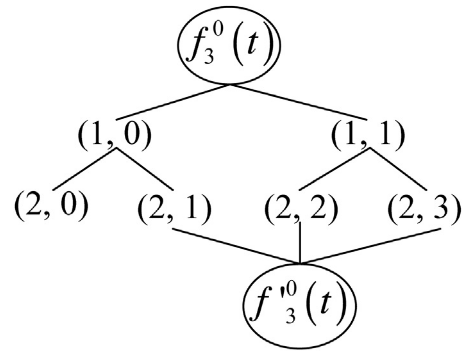

Fig. 2. The wavelet packet tree which is reconstructed to give back.

the PSD of the EEG is computed by Welch's method, and then the integrated power *IP* for a frequency band *b* is defined as [29]

$$IP(b) = \sum_{f=f_1^b}^{f_2^b} \mathrm{PSD}(f), \tag{1}$$

where$f_1^b$and$f_2^b$are the lower and upper cutoff edges of the band *b*, respectively. In this research, the integrated powers for the selected wavelet packet component signals are deployed as the characteristics to represent the variation of the power.

2.3.3. Pattern match regularity statistic (PMRS)

To understand how regular a time series is, Pincus [30] presents approximate entropy (ApEn) to quantify the complexity and the creation of information. The large value of ApEn represents high complexity for the time series. Considering a time series, denoted as$\{x_l, l = 1, \cdots, N\}$, the phase space R^m is reconstructed from this time series. A subsequence $X(i) = [x_i, x_{i+1}, \cdots, x_{i+m-1}](1 \le i \le N - m + 1)$ represents one of vectors in this phase space. For the computation of ApEn, the value match criterion is used to estimate the similarity between the vectors$X(i)$and$X(j)$, which is defined as

$$\max_{0 \le k \le m-1} |x(i+k) - x(j+k)| \le r, \tag{2}$$

where *r* is a threshold value. Note that for different values of *r*, the results of ApEn can be inconsonant. From this point of view, it can be seen that the value match criterion is sensitive to the selection of parameter *r*. However, even though two vectors are value matched to each other, they may have different patterns, respectively. In this case, these value matched pairs are meaningless in practice, since their patterns are different [24]. Therefore, the value match is replaced by pattern match criterion to evaluate

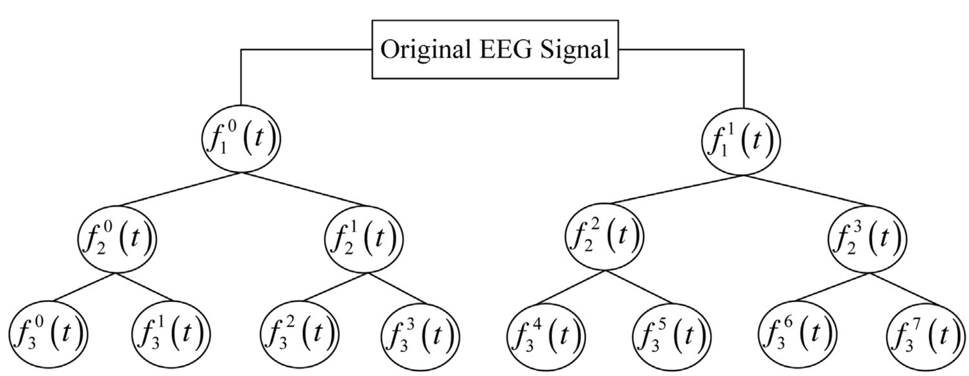

Fig. 1. The binary tree of the EEG data up to the third level of wavelet packet decomposition.

the complexity of a time series [24]. Only if two vectors $X(i)$ and $X(j)$ satisfy the following two conditions, these two vectors are considered as pattern matched to each other.

1) $|x_i - x_j| \le r$, and $|x_{i+m-1} - x_{j+m-1}| \le r$;

2) $\text{sign}(x_{i+k} - x_{i+k-1}) = \text{sign}(x_{j+k} - x_{j+k-1})$, $k = 1, 2, \cdots, m-1$

where r is a positive real number. The first condition shows that these two vectors must be in the same range. And the second condition shows that these two vectors must have the same pattern, i.e., pattern matched to each other. The pattern match regularity statistic (PMRS) [24] can be obtained from:

$$\text{PMRS} = -\frac{1}{N-m}\sum_{i=1}^{N-m} \ln\left(\hat{p_i}\right) \tag{3}$$

where $\hat{p_i}$ is the conditional probability that vectors $X(i)$ and $X(j)$ are pattern matched to each other.

Because of synchronous discharge of large groups of neurons during an epileptic seizure, the complexity in an EEG time series decreases. Hence the PMRS is deployed to quantify the regularity of EEG data in detecting seizure activities.

2.4. Imbalanced classification based on weighted ELM

Unlike the conventional gradient-based learning algorithms for a single hidden layer feedforward neural network (SLFN), the extreme learning machine (ELM) generates hidden nodes randomly, and then the output weights can be computed analytically [22]. Compared with the original ELM, the weighted ELM is able to provide additional emphasis to the samples, which are able to characterize the imbalanced class distribution, and defines an $N \times N$ diagonal matrix $\mathbf{W}$ associated with each of training samples [21].

Generally, if a sample $\boldsymbol{x}_k$ comes from the minority class, i.e. the category of seizure, the associated weight W_{kk} is relatively larger than others. Therefore, the optimization problem of the weighted ELM can be mathematically formulated as

$$\hat{\boldsymbol{\beta}} = arg\ \min\left(\frac{1}{2}\|\ \boldsymbol{\beta}\ \|^2 + \frac{1}{2}C\mathbf{W}\sum_{k=1}^{N}\|\ \boldsymbol{\xi}_k\ \|^2\right), \text{subject to } \mathbf{h}(\boldsymbol{x}_k)\boldsymbol{\beta} = \boldsymbol{t}_k - \boldsymbol{\xi}_k, \mathrm{k} = 1, \cdots, \mathrm{N}$$

where $\boldsymbol{\beta}$ is the output weight, $\mathbf{h}(\boldsymbol{x}_k)$ represents the hidden layer output, C is an added parameter for better generalization performance [31], and $\boldsymbol{\xi}_k$ denotes the training error of sample $\boldsymbol{x}_k$, which is calculated by the difference between the desired output $\boldsymbol{t}_k$ and the actual output $\mathbf{h}(\boldsymbol{x}_k)\boldsymbol{\beta}$. And then the solution of $\boldsymbol{\beta}$ can be derived by the method of Lagrange multipliers. It is written as

$$\hat{\boldsymbol{\beta}} = \left(\frac{\mathbf{I}}{C} + \mathbf{H}^T\mathbf{W}\mathbf{H}\right)^{-1}\mathbf{H}^T\mathbf{W}\mathbf{T} \tag{5}$$

where $\mathbf{H} = \begin{bmatrix}\mathbf{h}(\boldsymbol{x}_1)\\ \vdots \\ \mathbf{h}(\boldsymbol{x}_N)\end{bmatrix}$ is the hidden layer output matrix, $\mathbf{I}$ is the identity matrix and $\mathbf{T}$ denotes the target vector. The weight matrix $\mathbf{W} = \text{diag}\{W_{kk}\}, k = 1, \cdots, N$ determines the classification boundary that can be pushed towards the majority class. In this study, the class of seizure EEG samples is minority, while the non-seizure samples belong to the majority class. In this case, the weighting scheme is defined as

$$\begin{cases} W_{kk} = \eta/N_{seizure} if \boldsymbol{x}_k belongstotheseizureclass \\ W_{kk} = 1/N_{non-seizure} if \boldsymbol{x}_k belongstothenon-seizureclass \end{cases} \tag{6}$$

where $N_{seizure}$ and $N_{non-seizure}$ denote the numbers of samples belonging to the seizure and non-seizure classes, respectively. The value of η does not exceed 1.0. It is adjustable across different patients but must be fixed within one patient.

2.5. Postprocessing

In this work, the SLFN obtained using the weighted ELM algorithm has 40 hidden neurons, and the sigmoid function is chosen as the hidden layer activation function. There are two nodes in the output layer with specific target values defined as (1, 0) or (0, 1) for the seizure or non-seizure epochs, respectively. However, the actual output values of these output nodes are not equal to 0 or 1 but the continuous decision variable. In order to suppress the chattering characteristics caused by artifacts, a moving average filter is deployed to smooth the decision variable for the consecutive EEG epochs. The moving average filter is defined as:

$$z(n) = \frac{1}{2M+1}\sum_{m=-M}^{M} g(n+m) \tag{7}$$

where g denotes the input signal, i.e. the decision variable yielded from one of the two output nodes in the SLFN, z denotes the output data, i.e. the smoothed decision variable, and $2M+1$ is named as the smoothing length, which is patient specific. For the smoothed output values (i, j), if $i \ge j$, it is labeled as (1, 0), otherwise as (0, 1).

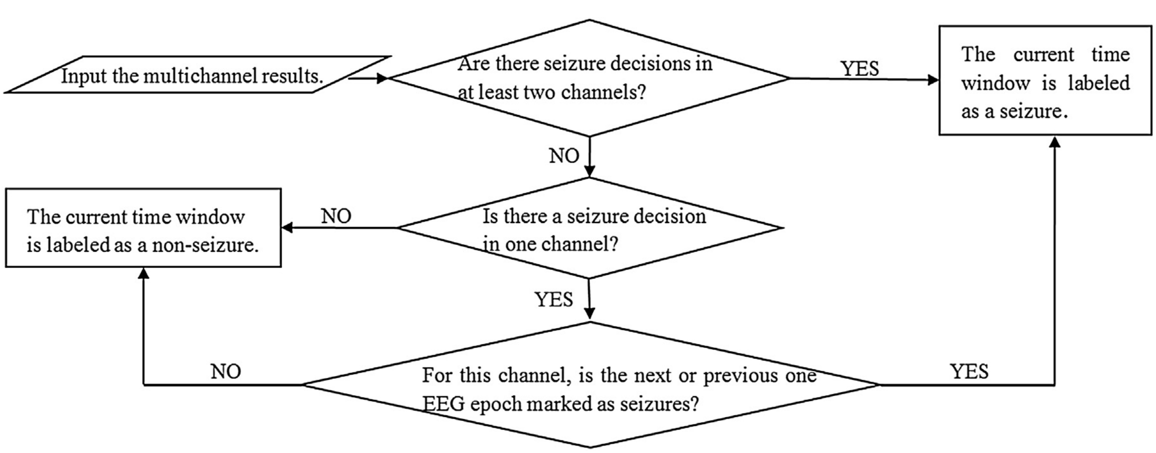

Fig. 3. The flow diagram of integrating the judgment results from the six parallel channels.

There are six channels available for the multichannel EEG recordings used in this study. The temporally parallel epochs come from the same time window, which is decided according to the steps of the procedure as illustrated in Fig. 3. Since the smoothing process may make the seizure epochs in the onset and retreat stages decided as non-seizures incorrectly, hence, a collar technique [32] is applied to compensate for the incorrect decisions on seizure events. According to the rules of collar technique, each detected seizure event is extended on both sides by l segments, i.e. $(l \times 4)$ s. In this work, the value of l is 3.

3. Results

All the EEG data are processed using MATLAB. For the aim of seizure detection, the moving-window technique is used to divide the long-term EEG data into epochs of 4-s each, and then the epochs are analyzed in a time sequence order. When an EEG epoch comes, the WPT decomposes the EEG epoch into the wavelet packet component signals, and then the features in terms of relative amplitude and integrated power are extracted from the selected component signals. At the same time, the nonlinear feature of PMRS is calculated from the original epoch. Thus, a nine-dimensional feature vector can be built up using the obtained features for each EEG epoch. The feature vectors of EEG epochs from different channels within the same time window are simultaneously input into the weighted ELM for classification. Finally, the post-processing techniques as described in Section 2.5 are used to make the decision for the EEG epochs on time window basis.

For a given patient, the training set is utilized to compute the weights of the SLFN by the means of the weighted ELM, while the validation set is used to tune the parameters, i.e. η of the weighted ELM and the smoothing length for post-processing. Finally, the performance of the fully specified decision model, which generates an acceptable sensitivity on the validation set, is evaluated by the testing set.

The assessment compares the seizure/non-seizure labels of the EEG epochs marked by the proposed algorithm with the parameters given by the EEG experts. The traditional statistical measures of sensitivity and specificity are calculated and defined as follows:

- Sensitivity is defined as the ratio of the number of true positives over the total number of seizure epochs marked by the EEG experts. Here, the term of true positive denotes an epoch marked as seizure by both of the algorithm and the EEG experts.
- Specificity is defined as the ratio of the number of true negatives over the total number of non-seizure epochs marked by the EEG experts. Here, the term of true negative denotes an epoch labeled as non-seizure by the algorithm and also identified as non-seizure by the EEG experts.

Furthermore, considering the imbalanced class distribution of the EEG epochs, after the computations of the sensitivity and specificity, the final result to measure the functionality of the presented method is the geometric mean of these two measures [21]. And this evaluation metric is called G-mean, which is defined as follow:

$$\mathrm{G-mean} = \sqrt{\mathrm{Sensitivity} \times \mathrm{Specificity}} \quad (8)$$

Table 2 lists the experimental results of the epoch-based assessment for the performance of the proposed method. It can be seen that, as indicated by the last row in Table 2, the average values of sensitivity, specificity and their G-mean are greater than 92.00% for all the 19 patients. Especially, the best sensitivity of 100.00% is achieved for patient #1, #3, #4, #6, #7, #9, #11, #12, #14, #18, and #19, respectively, which is 57.89% of all the patients. Fig. 4 illustrates an unsuccessful case, in which the seizure epochs were missed due to unobvious epileptic activities. From Table 2, it can be seen that except the five patients, including patient #5, #9, #10, #15 and #19, the other patients all have the specificity value above 91.00%. The reason is that the most of the false detections may be caused by the seizure-like activities, such as sharp jumps in amplitude and high amplitude activities. In fact, the smoothing filter in the post-processing is able to reduce the false detections as a certain extent, but it is helpless to reduce the false detections due to high amplitude activities as shown in Fig. 5.

The G-mean data shown in Table 2 indicate that there are only 4 patients, including patient #5, #10, #15 and #19, below 92.00%. Throughout an inspection, it has been found that the electrode box disconnection and reconnection affect the results for patient #10. When the results of patient #10 are discarded, the average sensitivity of 97.06%, specificity of 93.23% and their G-mean of 95.13% can be achieved for the other 18 patients.

Table 2
The results of the epoch-based evaluation for the performance of the proposed method.

Patient	Sensitivity (%)	Specificity (%)	G-mean (%)
1	100.00	95.98	97.97
2	94.29	99.98	97.09
3	100.00	95.35	97.65
4	100.00	94.72	97.33
5	89.13	88.84	88.99
6	100.00	99.32	99.66
7	100.00	96.15	98.06
9	100.00	86.06	92.77
10	71.92	73.99	72.95
11	100.00	99.92	99.96
12	100.00	99.60	99.80
14	100.00	94.07	96.99
15	90.10	71.59	80.31
16	90.59	97.70	94.08
17	98.53	99.68	99.10
18	100.00	96.85	98.41
19	100.00	72.17	84.95
20	86.08	98.34	92.00
21	98.44	91.83	95.08
Mean	95.74	92.22	93.96

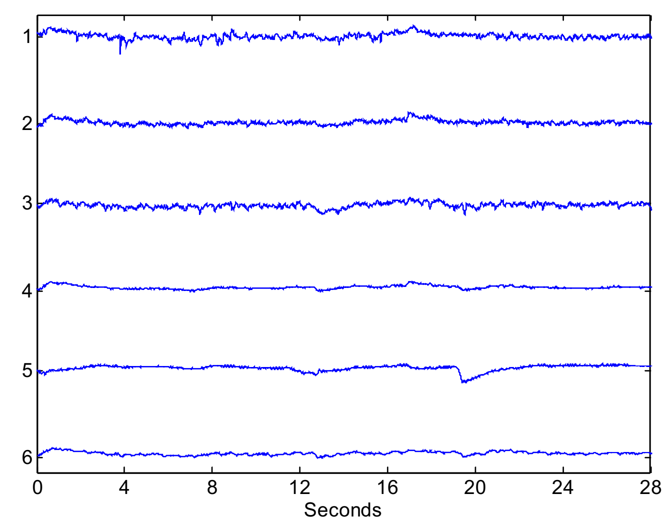

Fig. 4. An example of missed seizure signals from patient 5 due to unobvious epileptic activities.

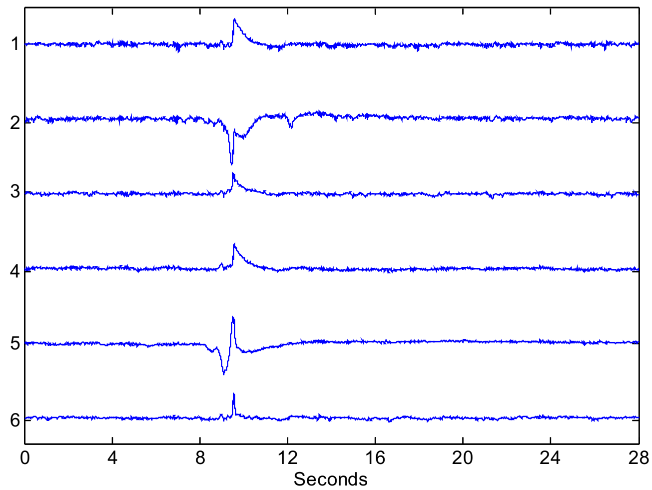

Fig. 5. An example of a false detection from patient 19 due to the short high amplitude activities.

It has been noticed that even if a seizure event is only partially detected by the automatic detection method, it can be still useful for neurologists in reviewing continuous EEGs in practical clinic application. Therefore, the event-based sensitivity is counted as another evaluation metric, which is defined as the ratio of the number of true detections over the number of total seizure events. Here, a single true detection is defined as a seizure event, which is overlapped with that labeled as seizure by the automatic detection method. Likewise, false detection is defined as the detected events, which are not identified as seizure events by the EEG experts. The false detections occurring less than 10 min after each other are considered as one single false alarm.

The results of the event-based investigation for the proposed method are listed in Table 3. It can be noticed by Table 3 that there is only one undetected seizure event with the patient #5. The false alarm rates for eight patients, including patient #2, #3, #4, #7, #11, #12, #17 and #21, are less than 0.10/hour, four patients, including patient #2, #4, #11, and #12, no false alarm and two patients, including patient #5 and #19, with a false alarm rate of 1.00/hour, which is caused by short-high amplitude activities due to artifacts. If patient #5 and #19 are abandoned, then the average false alarm rate falls to 0.30/h.

The mean detection latency between the algorithm-driven alarms and their actual seizure onsets that are marked by the EEG experts is 2.14 s for all the patients. If the detected onset is prior to the expert-labeled onset time, the latency can be set to zero. The performance evaluations presented by Tables 2 and 3 are able to demonstrate that the method proposed in this study has a great potential for the epileptic seizure detection to be applied in clinical application.

4. Discussion

In the development of this detection method, the ultimate purpose is to increase both the sensitivity and the specificity for the seizure detection system, as well as to guarantee the high event-based sensitivity. However, the sensitivity and specificity are defined as two technical specifications, which have the oppositional physical meanings against to each other. From this point of view, a high sensitivity value may trigger a decline in the specificity. Likewise, decreasing of the number of false detections may cause miss-detections of seizure events. More importantly, the class distribution of the EEG data is extremely imbalanced. By contrast, the regular learning algorithm has a natural tendency to prefer the majority class with an assumption of balanced class distribution. However, the fact is that the seizure data as the minority class may be misidentified as non-seizure. Therefore, the imbalanced classification is deployed to resolve the problem of seizure detection in this study.

The weighted ELM is not only combined with the original ELM by sharing several important merits, including fast training speed and good generalization performance, but also moderates the bias in performance caused by imbalanced class distribution. The principle of the ELM is to discover a boundary to distinguish the EEG feature samples between the seizure and non-seizure events with maximal marginal distance between these two categories, after the EEG feature vectors are projected onto the hidden layer space. In the case of the imbalanced EEG data, the separation boundary can be pushed towards the side edge of the minority seizure class, which tends to benefit the performance of the majority non-seizure class. By contrast, the weighted ELM is able to push the boundary backwards the majority non-seizure class by assigning a larger weight to the seizure samples from the minority class. Thus, the weighted ELM has a balance capability between

Table 3
The results of the event-based evaluation for the performance of the proposed method.

Patient	Number of true detections	Number of expert-marked seizure events	Sensitivity (%)	False alarm rate (/h)
1	2	2	100.00	0.84
2	1	1	100.00	0
3	3	3	100.00	0.04
4	3	3	100.00	0
5	2	3	66.67	1.00
6	1	1	100.00	0.43
7	1	1	100.00	0.04
9	3	3	100.00	0.73
10	2	2	100.00	0.57
11	2	2	100.00	0
12	2	2	100.00	0
14	2	2	100.00	0.68
15	2	2	100.00	0.72
16	3	3	100.00	0.25
17	3	3	100.00	0.06
18	3	3	100.00	0.11
19	2	2	100.00	1.00
20	3	3	100.00	0.54
21	3	3	100.00	0.08
Total	43	44	97.73	0.37

seizure and non-seizure classes, and yields overall optimum results in terms of geometric mean.

Furthermore, it is worth to note that the agreement between automatic seizure detection methodology and human evaluation of seizure events is often partial, which can be seen from the results reported in many published papers. On the one hand, since the visual inspection of EEG specialists is clearly influenced by their subjective experience, different EEG specialists may classify differently the same events. Hence, the visual inspection, which is regarded as "gold standard" in the performance evaluation of automatic detection, may be not very accurate. On the other hand, the characteristics of seizure events, such as duration, amplitude and repetition period are different from one event to another and also even during the same event occurrence. Therefore, this research combines the features related to both the time domain and frequency domain with a nonlinear descriptor to characterize the EEG data in order to achieve stable detection results.

The time domain and frequency domain EEG features are processed using the WPT technique, in which the decomposition procedure takes into account of both low and high frequency components. Hence, this general decomposition is able to cover a great range in frequency domain for EEG data analysis, which has significant advantages comparing to the DWT technique. The features of relative amplitude and integrated power can be used to describe the transition process, where the amplitude in time domain and the power in frequency domain, respectively. From Figs. 6 and 7, it can be observed that all the displayed values are increased significantly during the seizure events. This phenomenon indicates that the synchronous discharge of large groups of neurons during an epileptic seizure greatly boosts the energy of the EEG data at the selected nodes of the WPT.

It is well known that the brain electrical activities are very complex dynamic in nature. The EEG data derived from brain electrical activities reveal typically complex dynamic nature. The nonlinear feature in term of PMRS can describe the nonlinear behavior of the EEG data, and can quantify the complexity of the EEG data. This can be evidenced by the numerical results illustrated in Fig. 8 that the loss of complexity in EEG data due to seizure activities leads to the decrease of the PMRS values.

In this study, the invasive EEG data are utilized for the performance evaluation. Comparing to the scalp EEG data, the invasive EEG data have the advantages in terms of temporal resolution, bandwidth, signal-to-noise ratio (SNR) as well as the less vulnerable to artifacts such as electrooculography (EOG) and electromyography (EMG) [33]. Hence the preprocessing such as denoising and artifacts removing can be added before the WPT.

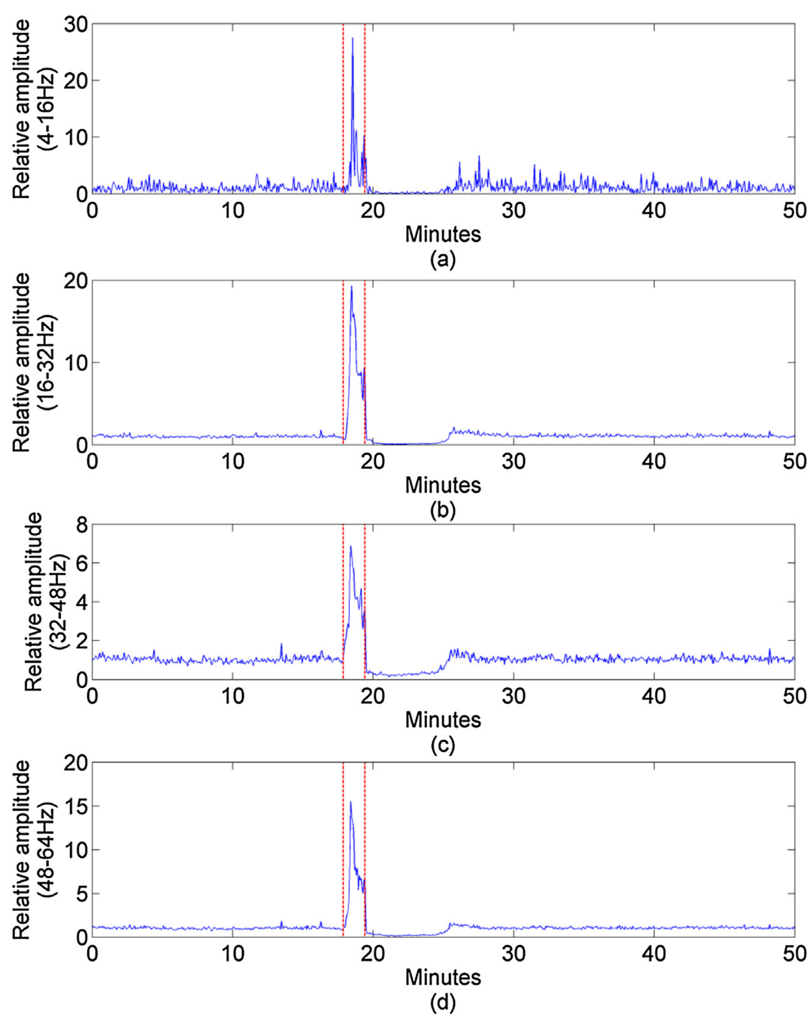

Fig. 6. The curves of the relative amplitude from the EEG data of patient 17, where the seizure event labeled by the EEG experts is between the two vertical dotted lines. (a)–(d) correspond to the curves calculated from the wavelet packet component signals, respectively.

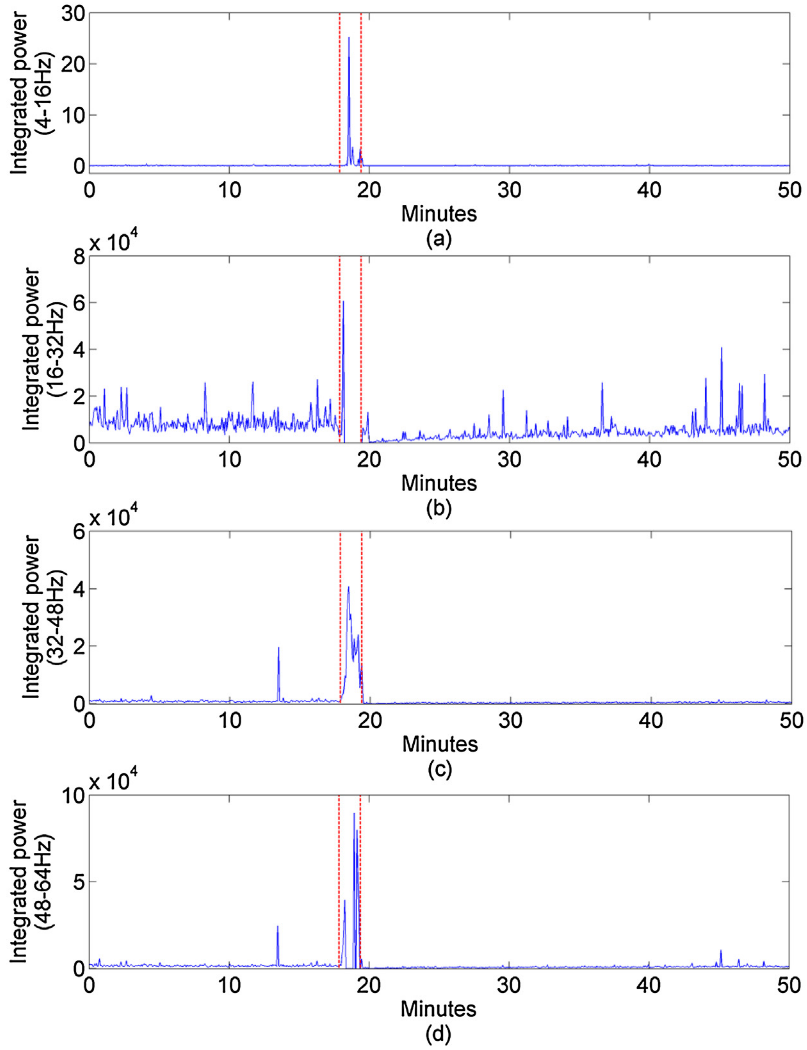

Fig. 7. The curves of the integrated power from the EEG data of patient 17, where the seizure event labeled by the EEG experts is between the two vertical dotted lines. (a)–(d) correspond to the curves calculated from the wavelet packet component signals, respectively.

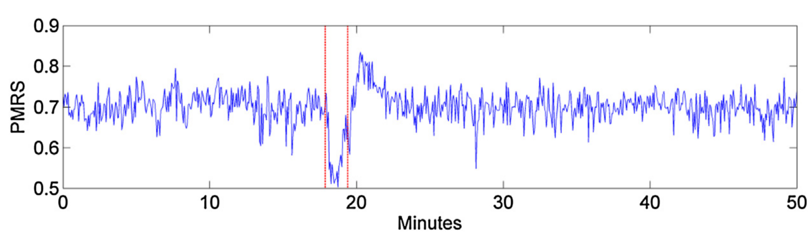

Fig. 8. The curves of the PMRS computed from the EEG data of patient 17, where the seizure event labeled by the EEG experts is between the two vertical dotted lines.

Furthermore, the processing approach proposed in this study will be applied to the investigation on the scalp EEG data in the future work.

There are a number of conventional approaches available for the epileptic seizure detection with different levels of success. Aarabi et al. [34] designed a fuzzy rule-based seizure detection system. Their system was evaluated on the same Freiburg dataset and achieved a sensitivity of 68.9% and a specificity of 97.8% in the segment-based assessment. So their G-mean could be estimated as 82.1%. In comparison to their work, this method improved the G-mean by 11.86%. Furthermore, a cascaded two-stage seizure detection algorithm proposed by Raghunathan et al. [35] utilized the DWT to separate the EEG data into the bands of interest, and then extracted the features which leaded to distinct “patterns” at the seizure onset. Their approach was only evaluated using 5 out of 21 patients, but its achievable G-mean was 93.46%, which was still lower than the approach presented in this paper.

Recently, the method presented by Zhang et al. [36] utilized the fractal dimensions as the features of EEG signals and employed the gradient boosting classifier to detect the abrupt changes of the temporal evolution of the EEG features. The G-mean of 90.93% was achieved by their method on the six-channel EEG data in the same Freiburg dataset. This method increased the G-mean by 3.03% compared with theirs. Although their false detection rate was

Table 4
Comparison of the performance between this method and other methods applied on the same dataset.

Method	G-mean (%)	Event-based sensitivity (%)	False alarm rate (/h)
A fuzzy rule-based seizure detection system [34]	82.1	98.72	0.81 before and 0.27 after false rejection
A cascaded two-stage seizure detection algorithm [35]	93.46	–	–
Fractal dimensions and gradient boosting classifier [36]	90.93	91.27	0.34
Wavelet decomposition of the prediction error signal and linear SVM [37]	–	95.0	0.124
Log-Euclidean Gaussian kernel-based sparse representation [38]	96.93	96.77	0.211
This work	93.96	97.73	0.37

slightly below that of this method, their event-based sensitivity was far smaller than 97.73% obtained by this method. Zhang and Parhi [37] used wavelet decomposition of the prediction error signal from a single channel to detect seizure activities by associated with the linear Support Vector Machine (SVM) technique able to achieve a false positive rate of 0.124/h which was smaller compared with that of this method. But the event-based sensitivity achieved by this method was better than theirs. The log-Euclidean Gaussian kernel-based sparse representation framework developed by Yuan et al. [38] for seizure detection yielded the slightly lower false detection rate of 0.211/h than that of this method. However, the event-based sensitivity obtained by this method was higher than theirs. Moreover, unlike their data selection rule, this study strictly used the first seizure event for training. Hence the experiments in this research work were all the prospective testing, but theirs might contain retrospective testing. The comparisons of this method and other methods applied on the same dataset are summarized in Table 4.

In addition, Tawfik et al. [39] combined the Weighted Permutation Entropy (WPE) and the SVM to discriminate the seizure and non-seizure EEG signals. The experimental data used in their work was got from the publically available Bonn dataset [40] which was much smaller than the Freiburg dataset used in this work. The average sensitivity of 89.5% and average specificity of 91.7% were yielded on the Bonn dataset contaminated with simulated artifacts applying the non-linear SVM classifier with overlapping window segmentation. Their G-mean of 90.6% was below the G-mean obtained by this method. In the work of Parvez and Paul [41], the various established transformations and decompositions were utilized to extract a number of statistical features, and the least square SVM was employed on the features for EEG classification. The 200 ictal and 800 interictal EEG signals from the Bonn and Freiburg dataset were used to evaluate the performance of their method. The G-mean of 88.17% from the average sensitivity of 92.93% and average specificity of 83.66% was achieved by combining all features in their experiments. By contrast, the amount of EEG data used in this research work was larger than that of theirs, and this method got the better G-mean compared with theirs. Donos et al. [42] employed a random forest classifier to discriminate a set of time domain and band power features for seizure detection. Their event-based sensitivity of 93.84% and false detection rate of 0.33/h were obtained on an EEG dataset containing 10 patients which was much less than the number of patients used in this work. Compared with their results, this method yielded the higher event-based sensitivity of 97.73% with a slightly increase in the false alarm rate.

Although the approach presented in this paper shows the better performance compared to other approaches mentioned above, but there is a limitation for the approach proposed in this paper to be directly applied in the clinical practice. The limitation is that seizures, epilepsies and diverse therapeutics have their specific influence on EEG signals, respectively, and these influences are certainly not in the same way. Thus, each seizure event is not always preceded or followed by the same signal transition, even if the patients are suffering from the same type of seizure. Moreover, the different types of seizures may also have different influences on the non-seizure EEG signals. In summary, the false detections may be inevitable for all existing automatic approaches.

5. Conclusions

In this study, a novel method based on the weighted ELM is proposed to detect seizure activities in long-term EEG recordings. The time and frequency domain features estimated on the component signals from the WPD and the nonlinear feature called PMRS are combined to characterize the behavior of the EEG signals. The weighted ELM is employed for the imbalanced EEG data classification by adding a weight matrix to weaken the impact of the majority non-seizure class while strengthen the impact of the minority seizure class. The G-mean of 93.96%, event-based sensitivity of 97.73% and false alarm rate of 0.37/h are achieved on the Freiburg dataset, which indicates its potential for the epileptic seizure detection in clinical practice.

Besides, the Freiburg dataset that contains widely varieties of patients and seizures is the benchmark resource in automatic seizure detection methods. The seizure types of each patient have been offered in this dataset; however, there is no clear information about the corresponding type of each seizure. Due to the lack of a sufficient number of each seizure type in the Freiburg dataset, it is planned in future to evaluate the performance of this method using much larger amounts of true continuous EEG data.

Conflict of interest

None of the authors have any conflicts of interest to disclose.

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