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Automatic Epileptic Seizures Joint Detection Algorithm Based on Improved Multi-Domain Feature of cEEG and Spike Feature of aEEG

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ABSTRACT Epilepsy is a disease in which patients undergo seizures caused by brain functionality disorder. Clinically, it is usually diagnosed by experienced clinicians according to continuous electroencephalography (cEEG), which is time consuming even for experienced doctors. Meanwhile, amplitude integrated electroencephalography (aEEG) has shown potential to detect epileptic seizures. Therefore, the paper proposes a hybrid seizure detection algorithm by combining cEEG-based seizure detection algorithm and aEEG-based seizure detection algorithm to detect seizures. In cEEG-based seizure detection algorithm, cEEG signals are divided into 5 s epoch with 4 s overlap and multi-domain features are extracted from each epoch. Then random forest classification is applied to do seizure detection. In aEEG-based seizure detection algorithm, morphological filter is applied to do spike detection and determine whether there are seizures after transforming the cEEG signals into aEEG signals. In order to evaluate the generality of the proposed method, experiments are performed on two independent datasets, including a publicly available EEG dataset (CHB-MIT) and an epileptic dataset collected by using the EEG device developed by the Hangzhou Neuro Science and Technology Co., Ltd. In the CHB-MIT dataset, the accuracy (AC), specificity (SP), sensitivity based on the event (SE), and false positive ratio based on the event (FPRE) obtained by the hybrid method are 99.36%, 82.98%, 99.41%, and 0.57 times/h, respectively. In the dataset we collected, the AC, SP, SE, and FPRE obtained by the hybrid method are 99.23%, 89.47%, 99.23%, and 0.71 times/h, respectively. The experimental results show that the performance of the proposed method is competitive with state-of-the-art methods and results. Furthermore, basing on the hybrid method, this paper has developed a portable automatic seizure detection system, which can reduce the burden of clinicians in processing the large amounts of cEEG signals by detecting seizure automatically.

INDEX TERMS Seizure detection, multi-domain feature, spike detection, hybrid method.

I. INTRODUCTION

Epilepsy is a disease in which patients undergo seizures caused by brain functionality disorder [1]. It affects approximately 9 million people in China and more than 65 million people worldwide [2]. Even worse, it can begin at any age [3]. In the clinical practice, diagnosing epilepsy is commonly implemented by continuous electroencephalography (cEEG), amplitude integrated electroencephalography (aEEG), Neurologic examination, CT scan, MRI, fMRI, PET scan and etc. [4]. In the aforementioned types of tests for diagnosing epilepsy, cEEG and aEEG are currently the two main methods

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for detection of epileptic seizures. cEEG is a graphical record of ongoing electrical activity in term of voltage fluctuations of the brain through multiple electrodes. It is considered as the gold standard for evaluating EEG background and detecting epileptic seizures [5]–[7]. aEEG, a processed, filtered and time-compressed electroencephalogram that presents amplitude (y-axis) over time (x-axis), has shown potential to detect epileptic seizures [8], [9]. However, more than 75% of people living in developing countries do not receive the treatment they need for their seizures and approximately 1 out of 3 individuals with epilepsy continues to experience frequent seizures despite of treatment of multiple anti-epileptic drugs [4]. Considering the serious outcome caused by epileptic seizures for the patients and the large population affected by epileptic seizures, it is necessary to develop rapid, robust and cost-effective seizure detection system.

Recently, many researchers focused on extracting features such as wavelet features [10], entropy [11], line length [12], and fractal dimension [13] from EEG signals for epileptic seizures detection. These features can then be combined with various classifiers, such as support vector machine [14], artificial neural network [15], [16], fuzzy logic model [17], Markov modeling [18] to identify the occurrence of seizures. In the CHB-MIT scalp EEG database [19], Samiee *et al.* [20] employed a novel feature extraction method which based on the sparse rational decomposition and the Local Gabor Binary Patterns (LGBP). The experiment result showed that the proposed technique outperforms other dedicated techniques by achieving the overall sensitivity of 91.13%. Shanir *et al.* [21] proposed a novel morphological feature extraction technique based on the local binary pattern (LBP) operator, combining with K-nearest neighbor algorithm to do seizure detection. As a result, mean accuracy of 99.7% and mean specificity of 99.8% were obtained. Orosco *et al.* [22] developed a patient non-specific strategy for seizure detection based on Stationary Wavelet Transform of EEG signals, and the mean values of specificity, sensitivity and false positive rate per hour parameters of the proposed offline method reached 99.9%, 87.5% and 0.9, respectively.

In parallel, aEEG is increasingly used in seizure diagnosis since several studies have proved to be useful for seizure detection [23], [24]. Lommen *et al.* [23] developed an algorithm for the automatic screening of electrographic neonatal seizures (ENS) with aEEG signals, the evaluation of the algorithm was based on 8 different cerebral function monitor recordings annotated by observer1 and an independent neurophysiologist, observer2. Finally, the algorithm showed in five recordings a sensitivity no less than 90% and approximately 1 false positive ENS per hour and in three recordings much lower sensitivities. Bourez-Swart *et al.* [24] compared the seizure pattern detection rate of single-channel and multichannel aEEG, using conventional EEG as a gold standard, in full-term neonates with hypoxic-ischemic encephalopathy. The results showed that the detection rate of epileptic pattern in multi-channel aEEG was slightly better than that in single-channel aEEG. Multi-channel aEEG identified correctly all patients with more than 1 seizure pattern in the small selection of patients. Clearly, the existing methods mentioned above are effective in the classification of epileptic seizures on specific databases. However, the performance may be unsatisfactory when the methods are used on different databases, due to the complexity of EEG signals and their feature diversity of different databases. In addition, to the best knowledge of authors, few studies have combined cEEG signals with aEEG signals for EEG seizures activity classification, so this paper integrates them into a unified framework to show their potential for seizure detection. However, considering the aEEG is compressed in time to display peak-to-peak amplitude values of filtered and rectified EEG, the proposed hybrid method is more suitable for epilepsy in which seizure events last for more than 10 s.

Basing on the above mentioned observation, this paper proposes a hybrid seizure detection method by considering the epileptic features of cEEG and aEEG and evaluates the generality of the proposed method by two independent datasets. For cEEG, the paper employed a new feature extraction strategy that extracts multi-domain feature of multi-channel EEG signals combined with random forest (RF) classifier for seizure detection. For aEEG, the paper applies morphological filter to do spike detection and determine whether there are seizures. Finally, the paper combines cEEG-based seizure detection algorithm and aEEG-based seizure detection algorithm to detect seizures jointly. Specifically, firstly, the paper uses the multi-domain features of cEEG signals with RF classifier for seizure detection. In parallel, the paper uses morphological filter to extract separate spike feature of aEEG to perform seizure detection. Then, if the same epoch is still in the state of seizure again, the event where the epoch is located is considered as a seizure.

The remainder of the paper is organized as follows. In Section II, the datasets used in this study and the proposed method of seizure detection are described in detail, including data preprocessing, feature extraction and classification techniques, and then further applications of the proposed system are discussed. Then in Section III, the evaluation procedure and the obtained experimental results are presented. Finally, further discussion and conclusions are included in Section IV and Section V.

II. MATERIALS AND METHODS

The paper proposes a hybrid seizure detection method that based on cEEG and aEEG, following the step of data preprocessing, feature extraction, RF training, spike detection, methods merging and implementation of the proposed method to a server for seizure detection. A detailed flowchart of proposed system is shown in Figure 1.

A. DATASET DESCRIPTION

To verify the generalization of the proposed method in this paper, two independent datasets were used, one is public dataset (CHB-MIT scalp EEG database), denoted as

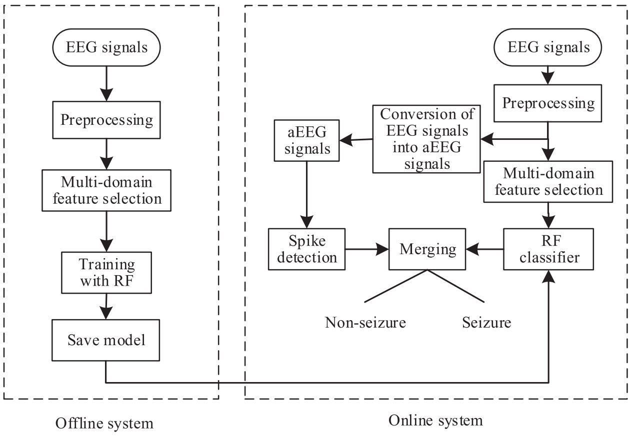


FIGURE 1. Flowchart of hybrid seizure detection system.

dataset A, and the other is EEG data collected by using the EEG device developed by Hangzhou Neuro Science and Technology Co., Ltd., which is denoted as dataset B.

The dataset A in this study comes from the CHB-MIT scalp EEG database which is described in Ali Shoeb's study [25] and access to the raw EEG recordings are possible in [19]. This dataset was collected at the Children's Hospital Boston, consisting of EEG recordings from pediatric subjects with intractable seizures. There are 24 patients involved in the dataset, including 5 males aged from 3 to 22 years old and 18 females aged from 1.5 to 19 years old. For each patient, long-term EEG data are recorded in continuous segments of 1 to 4 hour duration. All the signals were recorded with the sampling rate of 256 Hz and 16-bit resolution. Most cases contain 23 EEG signals derived from electrodes placed according to International Federation of Clinical Neurophysiology 10-20 placement system. While the recordings were being made, EEG signals were classified as epileptic seizures and non-seizures by experienced clinicians. A detailed description of the dataset A is shown in Table 1.

The dataset B for this study was collected by Department of Neurology, Epilepsy Center, Second Affiliated Hospital School of Medicine, Zhejiang University. 24 electrodes which included ground electrode and reference electrodes were placed on the scalp according to 10-20 system standard to do EEG collection. All the signals were recorded with the sampling rate of 500 Hz and the resolution of 24 bits. As a result, 21 channels were obtained, including 'EKG', 'FP1-Ref', 'FP2-Ref', 'F7-Ref', 'F3-Ref', 'FZ-Ref', 'F4-Ref', 'F8-Ref', 'T3-Ref', 'C3-Ref', 'CZ-Ref', 'C4-Ref', 'T4-Ref', 'T5-Ref', 'P3-Ref', 'PZ-Ref', 'P4-Ref', 'T6-Ref', 'O1-Ref', 'O2-Ref', 'OZ-Ref' where 'Ref' is the reference electrode. In order to facilitate data processing and subsequent model construction, it is necessary to adjust the data in dataset B to be the same format of selected channels of EEG in dataset A. For example, we can get 'F7-T3' by calculation of 'F7-Ref' - 'T3-Ref'. Finally, the paper collected EEG data of 5 patients with 291 .edf files. The seizure events

TABLE 1. CHB-MIT EEG dataset.

Case	Gender	Age (year)	Number of event	Duration (hour)
chb01	F	11	7	40
chb02	M	11	3	35
chb03	F	14	7	38
chb04	M	22	4	156
chb05	F	7	5	39
chb06	F	1.5	10	66
chb07	F	14.5	3	67
chb08	M	3.5	5	20
chb09	F	10	4	67
chb10	M	3	7	50
chb11	F	12	3	34
chb12	F	2	40	23
chb13	F	3	12	33
chb14	F	9	8	26
chb15	M	16	20	40
chb16	F	7	10	19
chb17	F	12	3	21
chb18	F	18	6	35
chb19	F	19	3	29
chb20	F	6	8	27
chb21	F	13	4	32
chb22	F	9	3	31
chb23	F	6	7	26
chb24	-	-	16	21

Gender: Female (F), Male (M)
Duration: approximation of total duration of EEG recordings
Event: a event represents a full epileptic seizures that last for a period of time

of EEG signals were marked by experienced clinicians. Table 2 shows the demographic information of dataset B. Moreover, Figure 2(a) and Figure 2(b) show segments of seizures and non-seizures, respectively. Clearly, when a seizure occurs, a group of EEG signals usually show a dramatic change from the non-seizure states. This will help to distinguish between seizures and non-seizures.

B. DATA PREPROCESSING

For dataset A, all recordings of subjects are stored in the files with the suffix .edf, and each case (chb01, chb02, etc.) contains 9 to 42 continuous .edf files from a single subject. In most cases, each .edf file contains about 1 hour of EEG signals, although those belonging to case chb10 are 2 hours long, and those belonging to cases chb04, chb06, chb07, chb09, and chb23 are 4 hours long; occasionally, files in which seizures are recorded are shorter. This paper selects the cases of chb01 to chb17 (TR) for model training and model tuning, and tests the model with the cases of chb18 to chb24 (TE). Conceptually, since the electrodes FP1 and FP2 are distributed near the eyes, they are more susceptible to interference from eye movements. In order to eliminate the effects of ocular artifacts on seizure detection, the paper removes the channels associated with FP1 and FP2, including 'FP1-F7', 'FP1-F3', 'FP2-F4' and 'FP2-F8'. According to international 10-20 system, channels 'P7-T7', 'T7-FT9', 'FT9-FT10' and 'FT10-T8' are removed. Therefore, this paper selects 14 channels from EEG signals of dataset A, including 'F7-T3', 'T3-T5', 'T5-O1', 'F8-T4', 'T4-T6', 'T6-O2', 'F3-C3', 'C3-P3', 'P3-O1', 'F4-C4', 'C4-P4',

TABLE 2. Demographic information of dataset B.

Patient_id	Gender	Age	Type of seizure	Anti-epileptic drug
Id1	F	24	focal seizures	Oxcarbazepine, Keppra, Sodium Valproate
Id2	F	37	tonic-clonic	Lamotrigine, Keppra
Id3	F	22	unknown type	-
Id4	M	37	left limb tonic-clonic	Lamictal, Carbamazepine
Id5	F	25	tonic-clonic	Keppra, Carbamazepine

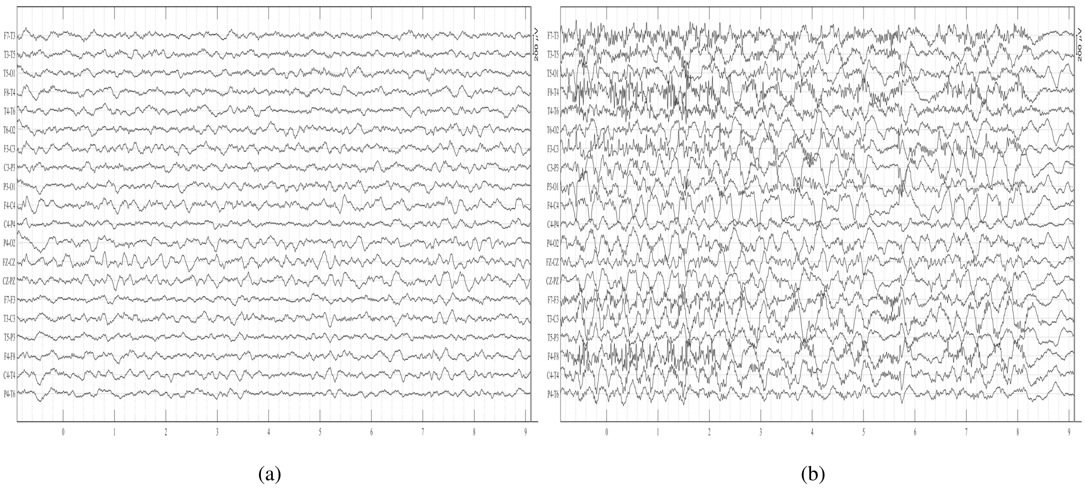


FIGURE 2. Non-seizure and seizure EEG signals. (a) EEG signals with non-seizure status. (b) EEG signals with seizure status.

'P4-O2', 'FZ-CZ' and 'CZ-PZ'. In order to get more information of EEG signals, another 6 channels ('F7-F3', 'T3-C3', 'T5-P3', 'F4-F8', 'C4-T4' and 'P4-T6') are calculated. The specific calculation method are shown in Eq (1) to Eq (6).

$$\text{'F7-F3'} = \text{'FP1-F3'} - \text{'FP1-F7'} \tag{1}$$
$$\text{'T3-C3'} = \text{'F7-F3'} + \text{'F3-C3'} - \text{'F7-T3'} \tag{2}$$
$$\text{'T5-P3'} = \text{'T5-O1'} - \text{'P3-O1'} \tag{3}$$
$$\text{'F4-F8'} = \text{'FP2-F8'} - \text{'FP2-F4'} \tag{4}$$
$$\text{'C4-T4'} = \text{'F4-F8'} - \text{'F4-C4'} + \text{'F8-T4'} \tag{5}$$
$$\text{'P4-T6'} = \text{'P4-O2'} - \text{'T6-O2'} \tag{6}$$

Clearly, dataset A is a set of EEG signals containing 20 channels. As continuous seizure onset last for a period of time, this paper aims to detect seizures that lasts for more than 10 s [26]. So this paper chooses 5 s long epochs with 80% overlap to detect epileptic seizures per second. However, after EEG signals are segmented, there will be a distinct data imbalance problem between epochs with seizure and epochs without seizure. By using statistical analysis, the duration of seizures is in the range of 6 s-752 s in dataset A, which is only a very small part of the monitoring EEG signals. Figure 3 shows the detailed distribution of seizures duration. It is easy to find that most seizures last for less than 200 s. Hence, in order to improve the performance of seizure detection, the paper removes all epileptic seizures with duration less than 10 s. In this paper, the number of .edf files with seizures and non-seizures in the case of chb01 to chb17 were

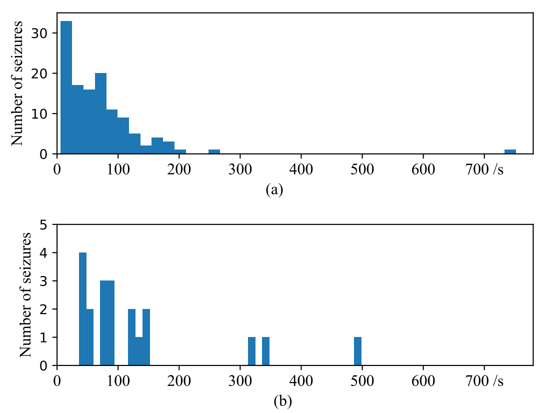


FIGURE 3. Distribution of seizures duration.

96 and 398, respectively. The paper selected 96 .edf files containing seizures as training sets. Further, considering that the number of seizures is not balanced with the number of non-seizures in these files after segmented, the dataset TR is preprocessed using a downsampling method to ensure the balance of the training dataset. Specifically, 6,620 seizure epochs were obtained from seizure data according to the aforementioned segmentation method, and then 6,620 non-seizure epochs were randomly selected from non-seizure data. Finally, the paper uses the aforementioned segmentation method to handle dataset TE, and obtains the number of seizure epochs and non-seizure epochs are 2,185 and 735,289 in 201 .edf files, respectively.

TABLE 3. Extracted features.

Category	Types	Feature parameters	Number
cEEG signals	Time	Kurtosis, Skewness, Max, Min, Mean	20×5
		Non-zero features of correlation	108
		Eigenvalues of correlation matrix between 20 channels	20
		Max, Min and Mean in the left front area	3
		Max, Min and Mean in the left rear area	3
		Max, Min and Mean in the right front area	3
		Max, Min and Mean in the right rear area	3
	Frequency	Eigenvalues of correlation matrix between 20 channels	20
		Non-zero features of correlation	108
		Amplitude in frequency domain with 1-48 Hz bandpass filter	20×48

For dataset B, similarly, we store it as .edf file. Since the entire dataset B is used to test the performance of the proposed method, the data preprocessing method is the same to dataset TE, and obtains the number of seizures epochs and non-seizure epochs are 2,252 and 1,025,427 in 291 .edf files, respectively.

C. SEIZURE DETECTION WITH CEEG

1) FEATURE EXTRACTION

In order to improve the performance of seizure detection using cEEG signals, this paper mainly extracts 2 types of features. The first type is to extract features from the time domain of cEEG signals, and more importantly, according to the characteristics of seizures, this paper also proposes a concept of partition for feature extraction. The second type is to extract features from the frequency domain of cEEG signals. All of the features extracted from cEEG signals are summarized as shown in Table 3.

- time domain
  The time-domain features extracted include 3 parts. The first part is the statistical features of each epoch of each channel, including kurtosis [27], skewness [28], Max, Min and Mean. Hence, 20 channels have a total of 100 statistical features in this part. The second part is the correlation coefficients between any two channels. Obviously, not all of correlation coefficients between channels have an effect on seizure detection, especially those that are far apart. Therefore, the paper introduces a regional correlation matrix consisting of 0 and 1, with 1 indicating that the two channels are adjacent in spatial position, and if they are not adjacent, they are represented by 0. Figure 4 shows the well-defined regional correlation matrix. In particular, in order to avoid selecting duplicate features, all the lower triangular elements of the regional correlation matrix is set to 0. Then we multiply the correlation matrix with the regional correlation matrix to obtain the final correlation features. Moreover, the paper also calculates the eigenvalues of the correlation matrix and 20 eigenvalues are obtained.

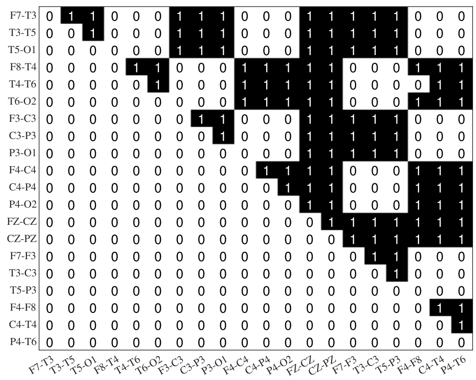


FIGURE 4. Regional correlation matrix.

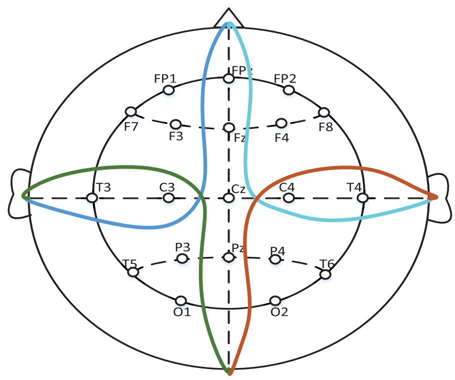


FIGURE 5. A schematic diagram of multi-channel partition.

As a result, 128 features are eventually obtained in this part. In the third part, since the onset of epilepsy usually originates from a certain part of the brain, including the left cerebral hemisphere, the right cerebral hemisphere, the forehead and the posterior lobe. Therefore, the paper divides it into 4 regions, as shown in Figure 5. Subsequently, the paper calculates the Max, Min, and Mean correlation coefficients of these four regions as part of the features and obtains 12 features.

- frequency domain
  In order to extract the synchronization character of EEG signal in frequency domain, the paper filters the EEG signal with a bandpass filter from 1 Hz to 48 Hz and applies and Fast Fourier Transform (FFT) algorithm to do signal transformation of each epoch data and get the amplitude of all the frequency component. And then the correlation coefficient of the amplitude in frequency domain of any two channels will be calculated.

2) CLASSIFICATION BASED ON RF

In proposed method, RF classifier is chosen to be used since it has shown good performance for seizure detection [29], [30]. On the one hand, since the dataset used by each tree in the RF is randomly sampled, it is not sensitive to the abnormal data; on the other hand, the final predicting result of the RF classifier is obtained by averaging all the trees, which is not easy to over-fit. RF classifier proposed by Breiman [31] contains multiple decision trees and its output category is determined by the highest number of votes given by all trees. Through bootstrap resampling technique, a new training sample set is generated by randomly selecting k samples repeatedly from the original training sample set N, and then a RF was generated from k individual decision tree classifier. The essence of RF classifier is an improvement of the decision tree algorithm. Multiple decision trees are merged together, and the establishment of each tree depends on an independently extracted sample. Each tree in the forest has the same distribution, and the classification error depends on each tree's classification ability and their correlation.

In this paper, the dataset A is divided into training set (6,620 seizures epochs and 6,620 non-seizure epochs) and testing set (2,185 seizures epochs and 735,289 non-seizure epochs in 201 .edf files). Next, input the 1,328 features listed in Table 3 into the RF classifier. This method of seizure detection is referred as E1.

D. SEIZURE DETECTION WITH AEEG

1) AMPLITUDE INTEGRATED EEG SIGNALS

In order to further improve the performance of seizure prediction, the paper converts the cEEG signals into aEEG signals and then detects the seizure by spike detection method. The processing of original EEG signals are mainly reflected in the following 3 aspects.

- Quadratic narrow-band asymmetric filtering
  aEEG firstly performs a 2-15 Hz quadratic narrow-band asymmetric filtering on the original cEEG data [32], filtering out fast waves with very low amplitude and very low frequency components that are not important for evaluating brain function, so as to analyze meaningful frequency ranges.
- Amplitude integration
  If the original cEEG signals are compressed directly in time axis, the very low amplitude component will be submerged in the high amplitude component and can not be recognized. Therefore, aEEG integrates the amplitude in a semi-logarithmic manner. Specifically, firstly, take the absolute value of the EEG signals amplitude to ensure that it is positive. Then, according to [26], the paper selects 5 μV threshold for amplitude integration. Hence, the values below 5 μV on the axis of ordinate are kept unchanged, and perform logarithm operation on the values above 5 μV.
- Time compression
  The time axis of the original cEEG signals are highly compressed by aEEG to highlight the macro trend. In this paper, considering that the data sampling rate in dataset A and dataset B are 256 Hz and 500 Hz respectively, the compression ratio are 256:1 and 500:1 respectively on the time axis, that is, the maximum value per second of the EEG signal is taken.

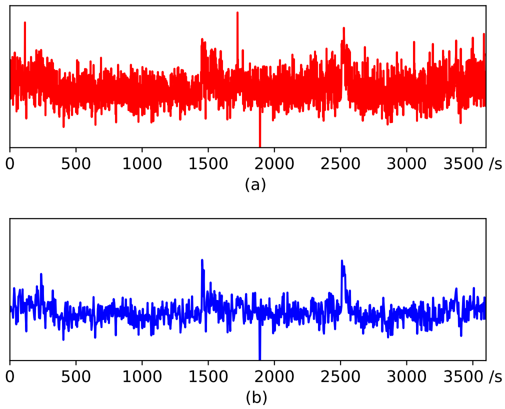


FIGURE 6. aEEG signal and corresponding lower envelope from chb20 (13.edf) in F7-T3 channel.

Finally, this paper takes a minimum value every 4 s for the aEEG signals to obtain the lower envelope of the aEEG signal for subsequent spike detection. Moreover, in order to visualize the aEEG signal and the lower envelope of the aEEG signal, Figure 6 show the transformed aEEG signal and envelope of aEEG signal from chb20 (13.edf) in F7-T3 channel.

2) SPIKE DETECTION METHOD

Generally, aEEG is extracted from original EEG by compression in time domain. Epileptic seizure evolves from onset to end with EEG wave that accentuate the background which will form spike shape wave in aEEG. The rising edge of the spike reflects the onset of seizure and the falling edge reflects the end of seizure. The process of seizure onset to end which lasts long enough (longer than 10 s) to form spike shape can be described by spike wave envelope. Hence, after obtained the lower envelope of the aEEG signals, a spike detection method [33] based on morphological filter is proposed to detect seizures in this paper. A morphological filter is a nonlinear filter that uses predefined structural elements to match signal lines and extract signals whose features are similar to them. Therefore, the detection of seizures can be regarded as

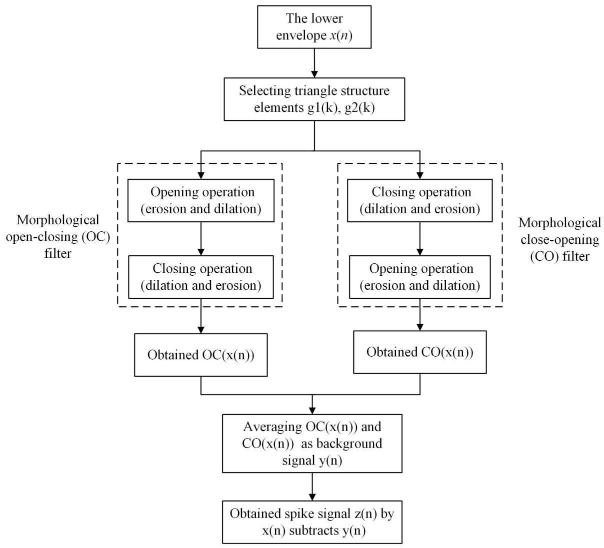


FIGURE 7. The flow chart of spike detection.

the detection of spike waves on the lower envelope of the aEEG signals. However, it can find the seizure lasts longer than 10 s which is long enough to form spike shape wave in aEEG. Figure 7 illustrates the method of the spike detection method.

According to Figure 7, the first step to detect spike waves in the lower envelope of aEEG signals is selecting a suitable function as the structural element, which has a great impact on the signal processing results. In order to remove the transient components in the lower envelope of aEEG signals and separate spike wave from background signals, the selected structural elements should be able to reflect the geometric characteristics of the lower envelope of aEEG signals, and its width should be between the spike waves period and the background signals period. Hence, the paper selects the triangle as the structural element. According to [34] and [35], the spikes with sharp peaks and polar upwards are called negative spikes and downwards are called positive spikes. Moreover, since the triangle is similar to the spike shape and its function is simple, only two parameters including width and height are needed to determine. Therefore, the triangle structure element $g(k)$ are selected in this paper. The function is shown in Eq. (7).

$$g(k) = A \cdot \left(1 - \frac{|k|}{L}\right), \quad k = -L, \ldots, 0, \ldots, L \tag{7}$$

where A is the height and L is half of the width.

In this study, the paper uses the average seizure time in dataset TE as the width of the spike wave, which is 46 s. Therefore, the value of L is 23 s. Moreover, the minimum and maximum wave peaks of the lower envelope of aEEG signals in dataset TE are taken as the range of A which is [8.5, 10]. In order to suppress the background signal further on, two set of structural elements are chosen according to Eq. (7) and the amplitude range of spike as shown in Eq.(8) and Eq.(9).

$$g_1(k) = 8.5 \cdot \left(1 - \frac{|k|}{23}\right), \quad k = -23, \ -22, \ldots, 23 \tag{8}$$

$$g_2(k) = 10 \cdot \left(1 - \frac{|k|}{23}\right), \quad k = -23, \ -22, \ldots, 23 \tag{9}$$

Next, the cascade open-closing(OC) and close-opening(CO) operations in mathematical morphology are used to remove epileptic transient signals in the lower envelope of aEEG signals. And then an average weighted combination of OC and CO was utilized to eliminate statistical deflection of amplitude and extract the background signals. In this paper, it is stated $x(n)$, $(n = 0, 1, \ldots, N-1)$ denotes the lower envelope of aEEG signals and $g_i(n)$, $(i = 1, 2; n = 0, 1, \ldots, M-1)$ is the triangle structure element, N is the length of $x(n)$, $M = 45$. Then, the morphological erosion and dilation operations [36] of $x(n)$ on structural element $g_i(n)$, $(i = 1, 2)$ are defined as Eq. (10) and Eq. (11).

$$(x \ominus g_i)(n) = \min_{m=0,1,\ldots,2L-1} \{x(n+m) - g_i(m)\}, \quad (n = 0, 1, \ldots, N-M), \quad (i = 1, 2) \tag{10}$$

$$(x \oplus g_i)(n) = \max_{m=0,1,\ldots,M-1} \{x(n-m) + g_i(m)\}, \quad (n = M-1, M, \ldots, N-1), \quad (i = 1, 2) \tag{11}$$

where $\ominus$ and $\oplus$ represent erosion and dilation operations, respectively.

Then, the morphological opening operation and closing operation of $x(n)$ on structural element $g_i(n)$, $(i = 1, 2)$ are defined as Eq. (12) and Eq. (13).

$$(x \circ g_i)(n) = [(x \ominus g_i) \oplus g_i](n), \quad (i = 1, 2) \tag{12}$$

$$(x \bullet g_i)(n) = [(x \oplus g_i) \ominus g_i](n), \quad (i = 1, 2) \tag{13}$$

where $\circ$ and $\bullet$ represent opining and closing operations respectively.

As shown in Eq. (10) to Eq. (13), the opening and closing operations are the combinations of erosion and dilation. The opening operation can smooth the signal positive pulse (peak), while the closing operation can smooth the signal negative pulse (valley). In order to simultaneously remove the positive and negative pulses in the signals, the paper uses the method of Maragos [37], [38] to constructs morphological OC and morphological CO filter. Eq.(14) and Eq.(15) show the filter calculation method for morphological OC and morphological CO.

$$OC(x(n)) = x(n) \circ g_1 \bullet g_2 \tag{14}$$

$$CO(x(n)) = x(n) \bullet g_1 \circ g_2 \tag{15}$$

The paper assumes that the lower envelope of the aEEG is $x(n) = y(n) + z(n)$, $y(n)$ is the background signals which changes slowly, and $z(n)$ is a fast-changing transient signal, when $x(n)$ after OC operation and CO operation, the paper can get the background signal $y(n)$ through Eq. (16)

$$y(n) = \frac{1}{2}[OC(x(n)) + CO(x(n))] \tag{16}$$

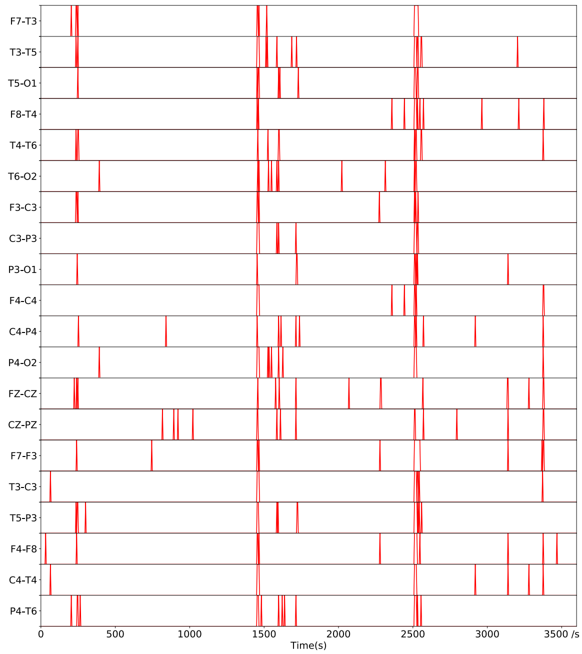


FIGURE 8. Extraction of spikes from aEEG signals from chb20 (13.edf).

Finally, the spike waves are detected from lower envelope of aEEG signals by subtracting the background signal from the original lower envelope signal. Spike signal $z(n)$ can be extracted by Eq. (17).

$$z(n) = x(n) - y(n) \tag{17}$$

In order to make the detection results of epilepsy clear and concise, the paper defines a binary signal $w(n)$ as follow:

$$w(n) = \begin{cases} 1 & z(n) \geqslant threshold \\ 0 & z(n) < threshold \end{cases} \tag{18}$$

where $threshold = \overline{z(n)} + \sigma(z(n))$, $\overline{z(n)}$ and $\sigma(z(n))$ are the mean and standard deviation of $z(n)$, respectively.

According to the spike detection method in Figure 7, the peaks detected on the lower envelope of the aEEG signal are as shown in Figure 8. As can be seen from Figure 8, not every channel can detect the exact location of the seizure, and some channels even have a lot of false detection results. Therefore, the seizures can be detected by the absolute majority voting method, and the result is shown in Figure 10(c). This seizure detection method is referred as E2.

E. SEIZURE DETECTION WITH CEEG AND AEEG

Typically, cEEG data are always contaminated by artifacts. Some artifacts are similar to seizures in shape and will result in false detection of seizures. Although aEEG can help to reduce the influence of artifacts on seizure detection to a certain extent, it will also lose a lot of information. For example, aEEG lacks time resolution and cannot analyze waveforms and frequency which can be handled by cEEG.

In summary, considering the advantages and disadvantages of cEEG and aEEG in seizure detection, the paper combines

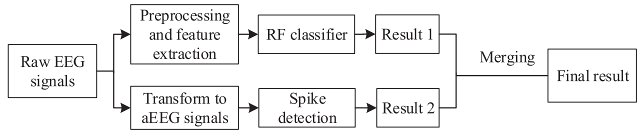


FIGURE 9. A hybrid framework for seizure detection.

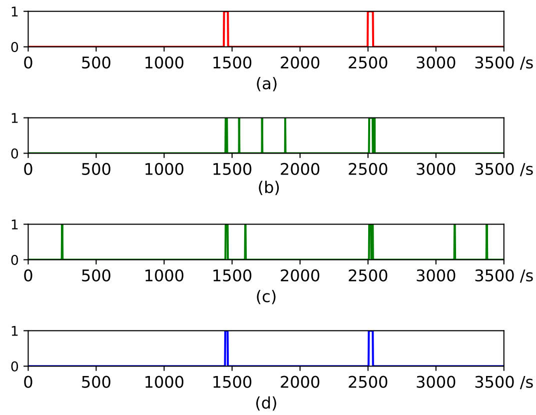


FIGURE 10. E3 for seizure detection. 1 represents seizures and 0 represents non-seizures. (a) 2 actual seizure events which are marked by clinicians occurs at about 1,441 s and 2,498 s, respectively; (b) 5 seizure events which are detected by E1 algorithm occurs at about 1,460 s, 1,552 s, 1,720 s, 1,890 s and 2,500 s, respectively; (c) 6 seizure events which are detected by E2 algorithm occurs at about 248 s, 1,452 s, 1,596 s, 2,508 s, 3,136 s, and 3,372 s, respectively; (d) two seizure events which are detected by E3 algorithm occurs at about 1,452 s and 2,508 s, respectively.

the advantages of these two methods of seizure detection to predict the occurrence of seizures. Figure 9 shows the hybrid framework for seizure detection. Firstly, the paper uses E1 to detect seizures, and the results are shown in Figure 10(b). Secondly, the paper uses E2 to perform seizure detection again, and the results are shown in Figure 10(c). If the same epoch is detected to be seizure by E1 and E2 simultaneously, the paper considers it as a seizure event, and the final results are shown in Figure 10(d). This method of seizure detection is referred as E3.

III. RESULTS

This paper evaluates the performance of the model from the perspective of machine learning and medical. From a machine learning perspective, classification accuracy based on epoch (AC), specificity based on epoch (SP) are calculated. From a medical perspective, the detection of a complete seizure event is more suitable for medical scenario application, so sensitivity based on event (SE) and false positive ratio based on event (FPRE) are calculated. Hence, this paper uses AC, SP, SE and FPRE to test the generality of the proposed method in dataset TE and dataset B. The proposed methods are implemented using python 3.5 with a workstation: Intel (R) Core (TM) i5-8400 CPU @ 2.58 GHz and 8 GB of RAM.

A. PERFORMANCE EVALUATION

In order to evaluate the generality of the proposed method, confusion matrix (CM) will be calculated to show the difference between the result given by the proposed method and the marks of experienced clinicians as shown in Eq. (19). S_{ij} represents the number of epochs that are marked to be class i and are classified to be class j. In the CM, seizures and non-seizures are represented to be class 1, and class 2.

$$CM = \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix} \tag{19}$$

According to CM, AC and SP can be calculated to evaluate the performance of the proposed method as shown in Eq. (20) and Eq. (21). Among them, the AC represents the percentage of correctly classified number of epoch of all testing epoch. SP is the rate of correctly detected non-seizure epochs against the actual number of non-seizure epochs detected by the proposed method. The higher the SP, the higher the detection rate of non-seizure.

$$AC = \frac{\sum_{i=1}^{2} S_{ii}}{\sum_{i=1}^{2}\sum_{j=1}^{2} S_{ij}} \tag{20}$$

$$SP = \frac{S_{22}}{S_{21} + S_{22}} \tag{21}$$

SE is the rate of correctly detected seizure event by the proposed method against the actual number of seizure event. Eq.(22) shows its calculation method. FPRE is the number of false alarms per hour and its calculation method is shown in Eq. (23).

$$SE = \frac{NUM_{detected}}{NUM_{actual}} \tag{22}$$

where $NUM_{detected}$ and NUM_{actual} represents the number of seizure events detected by the proposed method and the number of actual seizure events, respectively.

$$FPRE = \frac{FP}{H} \tag{23}$$

where FP represents the total event of false positive and H is the total duration of EEG recordings. An event represents the process from seizure onset to seizure end which lasts for a period of time, so an event may contain multiple epochs. In this paper, the number of non-seizures epoch is much larger than that of seizure epoch, so FPRE can better reflect the performance of the proposed method from actual medical practice.

B. TESTING AND VALIDATION RESULTS

In the CHB-MIT dataset, the paper implements E1, E2 and E3 to obtain a intuitive display of the results of seizure detection as shown in Figure 10. It can be clearly seen that the effect is not good when the E1 and E2 are used alone. It can be seen from Figure 10 that E1 detects 5 seizure events including 2 actual seizure events and E2 detects 6 seizure events including 2 actual seizure. When combining the advantage of E1 and E2, E3 detects only two actual seizure events without false detection which improves the detection performance obviously.

TABLE 4. Performance of different methods for dataset TE with training dataset TR.

Methods	AC (%)	SP (%)	SE (%)	FPRE (times/h)
E1	96.42	96.45	89.36	3.51
E2	98.92	98.94	89.36	0.94
E3	99.36	99.41	82.98	0.57

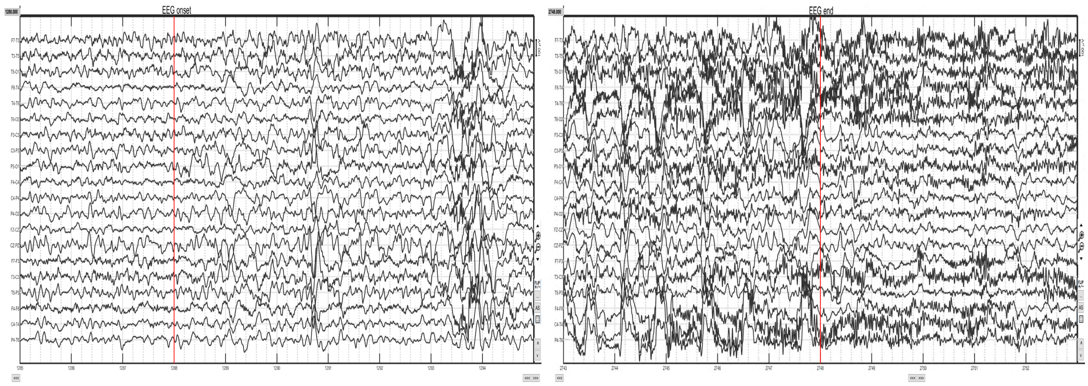
TABLE 5. Performance of different methods for dataset B with training dataset TR.

Methods	AC (%)	SP (%)	SE (%)	FPRE (times/h)
E1	95.52	95.54	89.47	9.11
E2	98.75	98.75	94.74	1.09
E3	99.23	99.23	89.47	0.71

In order to evaluate the generality of the proposed method, the paper uses AC, SP, SE and FPRE to evaluate the performance of the methods on two independent datasets. Table 4 and Table 5 show the AC, SP, SE and FPRE obtained by E1, E2 and E3 in dataset A and dataset B. It is easy to find that E3 is competitive with the E1 and E2 in both datasets, especially on AC, SP and FPRE. In dataset A, for AC and SP, E3 is about 3% higher than E1 and has a weak advantage over E2; for FPRE, E3 is much lower than E1 and has a weak advantage over E2. In dataset B, for AC and SP, E3 is about 4% higher than E1 and has a weak advantage over E2, while in terms of FPRE, E3 has a distinct advantage over E1. However, for SE, E3 is lower than E2 on both datasets. It can also be seen from Table 5 that mainly E1 leads to a decrease in SE, but significantly improves the AC, SP and FPRE.

Furthermore, in order to analyze the causes of seizures not detected by the method, the paper lists patient-by-patient results in Table 6 and Table 7. In Table 6, the case of chb21 has 4 seizures in actual case, but E3 did not detect seizures. Figure 11(a) describes the variation of EEG from non-seizure state to seizure state which are separated by a red division line. By observing EEG in Figure 11(a), it is easy to find that there is no sharp change in the EEG signal at seizure onset. The signal cannot be detected by aEEG, so E3 does not detect it. Likewise, Figure 11(b) describes the variation of EEG from seizure state to non-seizure state which are separated by a red division line. As shown in Figure 11(b), EEG signals in seizure state and non-seizure state show similar features which causes epileptic seizures in Id3 not detected.

Moreover, in order to better understand the impact of different window sizes (duration of an epoch) on the performance of the proposed method, Figure 12 shows the performance of the proposed method with different window sizes in dataset TE and dataset B. In Figure 12(a), It is can be seen that AC and SP (which are very close, almost coincidence) increase slightly with the increase of window sizes and tend to be flat when the window size is 5 s. Meanwhile, SE also achieves the optimum size in dataset B when the window size



(a) (b)

FIGURE 11. FP signals of chb21 and Id3. (a) FP signals of chb21. (b) FP signals of Id3. (c) FP signals of Id3.

TABLE 6. Patient-by-patient results of E3 for dataset TE.

Case	AC (%)	SP (%)	SE (%)	FPRE (times/h)	Actual	Detected
chb18	98.68	98.74	66.67	0.79	6	4
chb19	99.47	99.47	100	0.57	3	3
chb20	99.81	99.84	87.5	0.22	8	7
chb21	99.78	99.95	0	0.06	4	0
chb22	99.58	99.58	100	0.52	3	3
chb23	98.97	98.97	100	0.75	7	7
chb24	99.30	99.33	93.75	1.27	16	15
Overall	99.36	99.41	82.98	0.57	47	39

Actual : number of actual seizure event
Detected : number of seizure event detected

TABLE 7. Patient-by-patient results of E3 for dataset B.

Patient_id	AC (%)	SP (%)	SE (%)	FPRE (times/h)	Actual	Detected
Id1	98.75	98.75	100	1.22	4	4
Id2	99.25	99.25	100	0.79	2	2
Id3	99.62	99.65	75.00	0.30	4	3
Id4	99.61	99.64	75.00	0.41	4	3
Id5	98.97	98.97	100	0.56	5	5
Overall	99.23	99.23	89.47	0.71	19	17

is 5 s. However, in Figure 12(b), FPRE achieves the optimum size when the window size is 8 s. Figure 13 shows the runtime of the proposed method for different window sizes on dataset TE and dataset B. It can be found that the runtime of the proposed method is much longer than that of 5 s when the window size is 8 s. Hence, this paper finally chooses the window size of 5 s.

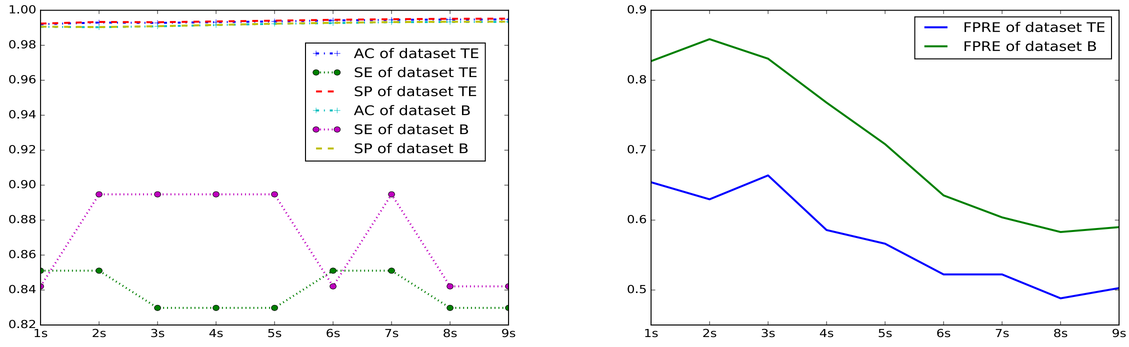
Finally, the paper compares the evaluation parameters of seizure detection methods proposed in this paper with the results reported in previous literature, and all of them are on CHB-MIT dataset. As it has been summarized in Table 8.

TABLE 8. Performance comparison in dataset A.

Methods	AC (%)	SP (%)	SE (%)	FPRE (times/h)
Nasehi et al. [39]. (2013).	-	-	**98.00**	**0.06**
Samiee et al. [20]. (2016)	-	99.10	91.13	0.35
Orosco et al. [22]. (2016)	-	**99.9**	87.5	0.9
Zabihi et al. [40]. (2016).	88.27	93.11	93.21	-
Selvakunmari et al. [41]. (2018)	96.77	97.97	95.01	-
Tsiouris et al. [42]. (2018).	-	-	88.00	8.1
Kostas et al. [43]. (2018).	-	-	95.1	10.13
proposed method (E3)	**99.36**	99.41	82.98	0.57

It can be observed that the AC calculated by E3 are higher than that of the same dataset in previous literature. However, the FPRE in the paper of Nasehi and Pourghassem [39] are much better than proposed method in this paper. By analyzing the paper of Nasehi and Pourghassem [39], it can be found that the dataset is divided into training dataset and testing dataset with EEG data of all the patients instead of different patients which can not show the performance of seizure detection of other patients whose epileptic EEG data are not available before testing. Moreover, it is non-trivial to note that the studies of Samiee *et al.* [20] and Orosco *et al.* [22] are not based on the whole CHB-MIT dataset, so FPRE and SP may be overestimated. Hence, E3 also has a significant improvement in the performance of FPRE. it is nearly 7 times/h lower than the study of Tsiouris *et al.* [42], and even 9 times/h lower than the study of Kostas *et al.* [43], which has obvious significance in medical diagnosis. In term of SE, because it is calculated from an medical perspective in an event-based manner, the result are lower than in most literature, but more suitable for medical scenarios.

In summary, the results of this paper indicate that E3 performs better than E1, E2, and other seizure detection methods in the literature in dataset A with the AC, SP and FRPE obtained by E3 are 99.36%, 99.41% and 0.57 times/h,



(a) (b)

FIGURE 12. Performance of proposed method in different window sizes. (a) Performance of AC, SP and SE with different window sizes. (b) Performance of FPRE with different window sizes.

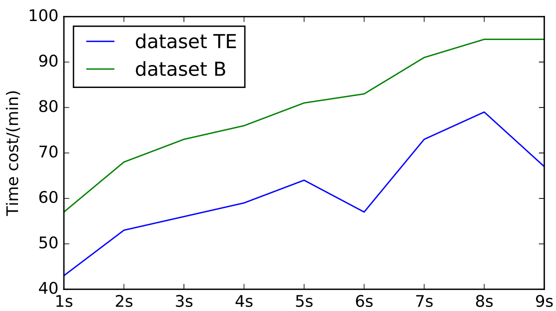


FIGURE 13. Runtime of proposed method in different window sizes. The overall length of dataset TE is about 205 hours and the overall length of dataset B is about 286 hours, so dataset B is above dataset TE.

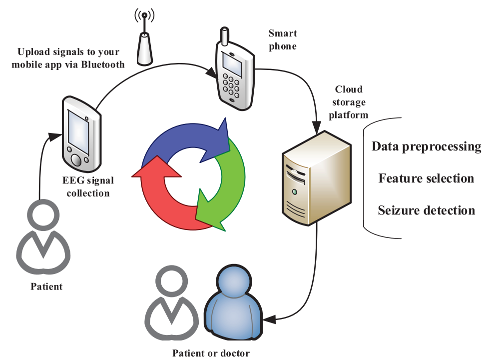


FIGURE 14. Schematics of the proposed system.

respectively. Moreover, the proposed method also shows good performance in dataset B, indicating that the proposed method behaves strong generalization.

C. APPLICATION OF PROPOSED SYSTEM

Since the proposed method is fully automated and can be easily implemented as a software application for the clinical diagnosis, a portable Automatic Seizure Detection System (ASDS) is developed. ASDS mainly includes 5 modules: data acquisition, data transmission, data preprocessing, feature selection and seizure detection. The system schematic diagram is shown in Figure 14.

In the ASDS, the portable EEG device developed by Hangzhou Neuro Science and Technology Co., Ltd. is used to collect EEG data at a sampling rate of 500 Hz. Figure 15 illustrates the method of collecting EEG data. In parallel, the collected EEG data is synchronized to the mobile APP via Bluetooth. Then the EEG data will be uploaded to the EEG cloud platform by through the mobile APP. And then, the hybrid method mentioned in this paper will be applied to detect seizures and return the diagnosis results to the mobile APP for convenience of patients or doctors to take medical measures. In general, it takes about 10 s for an hour of EEG data to get the results of seizure detection through the proposed system shown in Figure 14 but does not include the time required by the data transmission module, as this varies depending on the network.

FIGURE 15. Demonstration of collecting EEG data.

The ASDS allows patients to obtain high-quality medical resources at home without queuing in the hospital, which will improve patient experience and reduce medical costs. In addition, patients can get customized services from doctors and receive the latest medical advice.

IV. DISCUSSION

Various methods have been used to detect seizures [44]–[46], but most of them focus on feature extraction in cEEG signals.

In order to improve the performance of seizure detection, this paper combines cEEG signals with aEEG signals for EEG seizure detection. The FPRE of the proposed method reaches 0.57 times/h and 0.71 times/h on two independent datasets, respectively, indicating that the proposed method in this paper is an accurate tool in classifying the seizure epochs. In fact, the proposed feature extraction strategy from multi-domain based on multi-channel EEG signals can capture more discrimination information than a single EEG signal and the hybrid method can integrate the advantages of cEEG-based seizure detection algorithm with aEEG-based seizure detection algorithm. Hence, the main contribution of this study is the feature extraction strategy and hybrid method. Furthermore, basing on the proposed method, the paper has developed a portable ASDS, which can reduce the burden of clinicians in processing large amounts of cEEG signals through visual observation, and accelerate the diagnosis of epilepsy.

However, considering the aEEG is compressed in time to display peak-to-peak amplitude values of filtered and rectified EEG, the proposed hybrid method works well in condition that seizure events last for more than 10 s.

Moreover, the study in this paper is mainly focused on the detection of seizures and non-seizures by separating the EEG dataset into two classifications without considering the epileptic focus information. Further research can divide EEG data into more classifications such as non-seizure, preseizure, seizure and post-seizure. And also, the detection of epileptic focus information can be included in seizure detection.

V. CONCLUSIONS

The present study is undertaken to design an automatic seizure detection system based on cEEG signals and aEEG signals, and evaluate the generality of the system. In order to improve AC, SP, SE and FPRE of the proposed method, a new feature extraction strategy and hybrid method are proposed. Moreover, two independent datasets have been used to validate the performance of the proposed method. Particularly, the FPRE obtained by E3 reached 0.57 times/h and 0.71 times/h on two independent datasets, respectively.

VI. ETHICAL STANDARDS

This Study has been approved by the Second Affiliated Hospital of Zhejiang University and registered in Chinese Clinical Trail Registry (ChiCTR1900020726). All patients gave their informed consent prior to their inclusion in the study.

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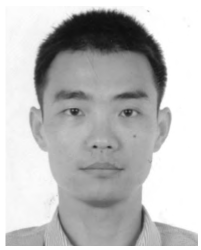

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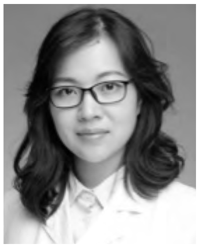

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