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Seizure detection algorithm based on improved functional brain network structure feature extraction

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ABSTRACT

Epilepsy is one of the most common neurological disorders. Accurate detection of epileptic seizures is essential for treatment. A seizure detection method with the structure of functional brain network, time, and frequency multi-domain features is presented in this paper. Pearson correlation coefficient (PCC) and mutual information (MI) can characterize the correlation between channels of EEG, and be used to construct PCC and MI combined functional brain networks (PMNet). Then the complex network theory is used to calculate the structure features of PMNet to explore whether it reflects seizure or not. After extraction of the multi-domain features, principal component analysis (PCA) is used to eliminate irrelevant feature information before feeding the features into the support vector machine (SVM) classification method. The method is tested on two open datasets (CHB-MIT and SIENA) and verified on the West syndrome (WS) dataset from the Children's Hospital, Zhejiang University School of Medicine. The results demonstrate that the method based on the structure of functional brain networks and other multi-domain EEG features is competitive with other comparison methods. Furthermore, base on the method with brain network features, this paper has developed a simple automatic seizure detection system in hospital applications, which can reduce the workload of EEG technicians in reading EEG and marking seizures.

1. Introduction

Epilepsy is a complex neurological disease caused by the abnormal discharge of neurons [1]. Accurate detection of epileptic seizures is essential for the treatment, controlling the dosage, and evaluating prognosis [2]. Electroencephalogram (EEG) can effectively indicate the neurophysiological damage caused by epileptic activity. Researchers have conducted extensive research on EEG signal analysis for seizure detection [3,4]. The feature extraction and classification of EEG signals are recognized as critical issues in seizure detection [5].

Due to the large amount and high dimension of EEG data related to epilepsy, the applications of feature extraction and classification technology are challenging tasks in seizure detection [6,7]. In the past few years, more and more attention has been paid to the application of machine learning classifiers in extracting meaningful patterns from EEG signals, which helps to detect seizures [8], locate approximate epileptogenic zone [9] and assist in epilepsy diagnosis [10]. We also believe that another significant challenge is how to design seizure methods and application systems according to the specific demand of epilepsy diagnosis. For example, from the investigation in the department of neurology in children's hospital, we believe that epilepsy detection cannot become an independent module at this stage. However, it can effectively reduce the workload of EEG technicians. Therefore, when designing seizure detection algorithms and systems, more attention should be paid to improving the indicators such as missed detection rate. Although we firmly believe that artificial intelligence technology can one day be relatively independent and perfect to realize seizure detection and diagnosis, at this stage, we still need to conservatively explore and try the application of various algorithms in seizure detection. Therefore, this challenge is not purely academic but a combination of academic and engineering applications.

The physiological network represents a relevant toolkit that can potentially overcome the inherent limitations of traditional EEG analysis methods in the application of seizure detection [11,12]. In the direction of seizure detection, this paper proposes an improved seizure detection

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method with structure of functional brain networks and other multi-domain features. First, we extract the features of the time and frequency domains of the EEG signal. We build a Pearson correlation coefficient (PCC) and mutual information (MI) combined functional brain networks (PMNet) from each pair of EEG signal channels. Then, we use the network structure properties of average degree (AD), clustering coefficient (CC), characteristic path length (CPL), and modularity (MD) to calculate the structure features of PMNet. We use principal component analysis (PCA) to eliminate irrelevant feature information and reduce the time for training the model before feeding the features into the classification model. Finally, we use different supervised machine learning classifiers to test their reliability and effectiveness in seizure detection.

The remainder of this paper is organized as follows: In Section 2, the related backgrounds are described, including EEG feature extraction methods, automatic seizure detection methods, and especially the application of complex network theory in EEG analysis. Section 3 introduces the seizure detection method with brain network and other multi-domain features. Section 4 tests and discusses the method on CHB-MIT and SIENA datasets and verifies it in the West syndrome (WS) dataset from the Children's Hospital, Zhejiang University School of Medicine. Section 5 makes a brief summary on this paper and prospects for future work.

2. Related works

2.1. Feature extraction methods

EEG feature extraction methods can be divided into the time domain, frequency domain, time–frequency domain, and other non-linear methods [13–15].

The time domain method uses the EEG data to extract signal features on the time scale. Tessy et al. [16] extracted two time domain features, namely line length, and energy of EEG, and then used the quadratic discriminant method, K-nearest neighbor (KNN) method and linear discriminant classifier to propose a low-complexity automatic seizure detection algorithm. Wei et al. [17] proposed a time domain feature extraction method based on waveform morphology. This method extracted EEG waveforms according to merger principles, and the results are close to human visual interpretation. Wang et al. [18] proposed a spike detection algorithm based on the EEG signals of benign epilepsy with centro-temporal spikes (BECT) patients. They used a spike calibration matching method and a clustering algorithm to screen the suspected spike waveforms and constructed a seizure detection model.

The frequency domain method is also a commonly used EEG data analysis technique. The most common frequency domain methods include fast Fourier transform (FFT) [19,20], power spectral density analysis [21], and fast cosine transform [22], etc. Hu et al. [23] proposed a feature map of the average amplitude spectrum based on the 19 sub-bands of the EEG. They then extracted deep features with a shallow convolutional neural network (CNN). Finally, They proposed a seizure detection method with support vector machine (SVM). Ghayab et al. [19] proposed an epileptic EEG data feature extraction algorithm combining hybrid optimal allocation and spectral density estimation. They used SVM, quadratic discriminant analysis, and KNN to evaluate the extracted features.

Compared with the time domain method, the frequency domain method can quantitatively characterize the regular pattern of the overall spectrum change of the EEG signal, extract the particular spectrum characteristics of the EEG signal rhythm in a limited frequency band, and finally realize the automatic classification of the epileptic EEG signal. However, due to the non-stationarity of the EEG signal, the frequency domain method cannot reveal the local change pattern of the EEG signal in a specific period. Therefore, extracting EEG features from the time domain or frequency domain has significant limitations in practical applications.

The time–frequency domain method can simultaneously reflect the time-varying characteristics and frequency characteristics. Therefore, the time–frequency domain method can overcome the shortcomings of the time domain or frequency-domain method. The time–frequency domain methods include wavelet decomposition [24,25] and empirical mode decomposition [26,27], etc. Wang et al. [28] proposed a state detection of epilepsy method based on wavelet packet features of EEG signals and random forest (RF) classifier. Hu et al. [26] extracted the EEG features based on empirical mode decomposition and wavelet packet decomposition, which better described the signal representation in different periods.

In addition to the above three analysis methods, nonlinear analysis methods can also reveal the complex behavior of the system and extract the features. Nonlinear methods in EEG data analysis application include correlation dimension [29], maximum Lyapunov exponent [30], and entropy analysis method [31], etc. Shoeibi et al. [32] used a univariate feature measurement method based on nonlinear dynamics to extract the features of EEG segments. They designed a seizure prediction system with fuzzy entropy. Kang et al. [33] calculated the power predication density and the maximum Lyapunov exponent of the EEG. They then used the t-test and SVM classifier to quantify the performance of feature selection. The structural properties of functional brain networks can also be used as features [34].

Generally, extracting the practical features of the EEG under a single transform domain is difficult, and the classification performance is not ideal [35]. Therefore, researchers try to combine multiple methods to achieve the purpose of multi-domain information mining and obtain better classification performance.

2.2. Automatic seizure detection methods

The research on seizure detection can be divided into traditional machine learning classification and deep learning classification algorithms. Most seizure detection classification applications can be regarded as two-class classification problems (seizure period and non-seizure period) or three-class classification problems (preictal period, interictal period, and seizure period) [36]. The traditional machine learning method mainly extracts EEG features and combines traditional classifiers such as Bayesian classifier, SVM, KNN, and linear discriminator for classification [37,38]. While the deep learning method usually builds a deep end-to-end network. It uses the deep network to extract the deep features of EEG and train a suitable classification model [39,40]. Due to the size of medical datasets, computational cost, algorithm complexity, and the engineering basis of features, traditional machine learning, and deep learning methods have advantages in specific application scenarios. In addition to seizures, other applications such as EEG-based emotion recognition are also worth learning. Wang et al. [41] proposed spatial–temporal feature fusion neural network (STFFNN) to improve the individual difference performance. Subasi et al. [42] used a flexible analytic wavelet transform (FAWT) feature-based multiboost-SVM method to realize the application of detection. Malathi et al. [43] achieved fine performance of emotion prediction by using PCA and SVM.

2.3. Complex network theory in EEG signal analyzing

Complex networks (graph theory) have been considered as an essential method in neuroscience. Analyzing epileptic EEG signals only by time, frequency, and time–frequency domain features may lose the non-stationary nature of epileptic seizures. However, the method based on complex network theory describes the correlation pattern and hidden sight of brain activity and behavior mapping from non-linear non-stationary EEG [44]. The neural connection networks of the brain can be divided into structural brain networks [45] and functional brain networks [46]. The functional brain network is constructed based on the statistical relationship of the functional EEG

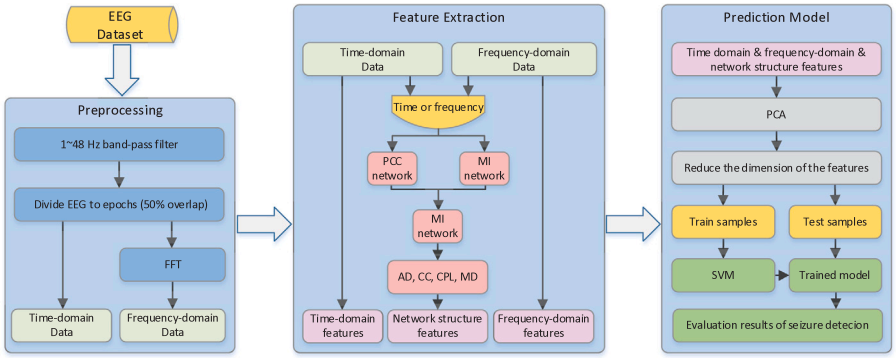


Fig. 1. The framework of the proposed method.

signals in a certain period [47]. In recent years, many researchers and clinicians have implemented complex network-based methods to detect epilepsy and other brain dysfunction from EEG, including time series complex network (TSCN) [48], recursive graph [49], horizontal visibility graph [50], and other methods.

Functional brain networks can be further used to analyze the causal relationship of EEG signals and reflect the direction of information propagation between electrode nodes. The first and critical issue is to use what kind of method to construct the functional brain networks. PCC is one of the simple and intuitive methods to construct functional brain networks [51]. Meanwhile, MI can also indicate the degree of correlation between two channels in the statistical distribution of energy [52]. Besides PCC or MI, the quantitative characterization of physiological networks has attracted widespread attention and has been applied in various applications [53]. Research shows that the brain and other physiological organs show a network synchronization phenomenon under specific conditions [54,55]. The brain has the synchronization phenomena during an epileptic seizure, and can be described as a brain network with FitzHugh–Nagumo (FHN) model [56]. Time delay stability [6], rhythms and their coupling patterns [57], correlation mode between frequency bands and regions [58] are more metrics that can be used to construct functional brain networks.

After establishing the functional brain networks, the specific measures of complex networks, such as degree distribution, clustering index, network efficiency, betweenness, and robustness of cascading failure, can be used to describe the characteristics of functional brain networks and reveal the efficiency of brain networks in different periods and provide a basis for the diagnosis of epilepsy. For example, Georgios et al. [59] discovered significant differences in the average degree, clustering coefficient and global efficiency between seizure and non-seizure periods, which can be used as a feature of seizure detection. Glennon et al. [60] found that the phase synchronization of various brain areas is significantly different before and after the seizure. In summary, the characteristic of complex network theory, such as network efficiency, transitivity, strength, average path length, clustering coefficient, etc., can effectively reflect the seizure situation [61,62].

3. Method

This paper proposes a multi-domain feature cross-fusion method. This method combines the time domain, frequency domain, and network structure domain to extract features of EEG and detect a seizure. Firstly, to extract the rhythm characteristic of EEG in the frequency domain and eliminate high-frequency interference, filter the EEG signal from 1 Hz to 48 Hz with a Butterworth band-pass filter, and calculate the energy at each frequency with FFT. Then divide the EEG signal into 1-second epochs (sliding window) and 50% overlap before and after each epoch. Secondly, extract the time domain and frequency domain features from each epoch. Thirdly, build brain PMNet based on the correlation matrix and mutual information from EEG channels in the time domain or frequency domain. And then extract the network structure indicators such as the network clustering coefficient, characteristic path length, and modularity as the features. After that, to reduce the complexity of feature dimensions and improve the classification results, use PCA to eliminate irrelevant feature information before sending the features into the classification model. Finally, use two different supervised machine learning classifiers to test their effectiveness and reliability of seizure detection. Fig. 1 is a flowchart of the proposed method.

Table 1
Time-domain statistical features.

Feature name	Definition
Kurtosis	$x_{kur} = \frac{\frac{1}{m}\sum_{i=1}^{m}(x_i - x_{mean})^4}{(\frac{1}{m}\sum_{i=1}^{m}(x_i - x_{mean})^2)^2} - 3$
Skewness	$x_{kur} = \frac{\frac{1}{m}\sum_{i=1}^{m}(x_i - x_{mean})^3}{(\frac{1}{m}\sum_{i=1}^{m}(x_i - x_{mean})^2)^{\frac{3}{2}}}$
Line length	$x_{ll} = \frac{1}{m}\sum_{i=1}^{m}\lvert x_{i+1} - x_i\rvert$
$1st$ quartile	$x_{Q1} = x_i$, where $i = \frac{1}{m+1}$
$3rd$ quartile	$x_{Q3} = x_i$, where $i = \frac{3}{4(m+1)}$

Note: x_i is the ith data value in a channel of EEG in an epoch with m length.

3.1. EEG features extraction

In clinical practice, EEG technicians usually distinguish abnormal EEG signals from amplitude, frequencies, and spikes, etc. Therefore, the extraction of statistical features in the time domain, frequency domain, and time–frequency domain conforms to a rule for the judgment of the EEG technician. Meanwhile, studying the structure of functional brain networks is a relatively new perspective to analyzing EEG signals. It explicitly shows a specific statistical relationship between the physiological records of different brain regions. Therefore, we extract time domain and frequency domain information to produce two functional brain networks, explore the network features and use them as key features to classify EEG signals and detect seizures.

3.1.1. Time domain features

The features extracted in the time domain are the statistical characteristics of each channel on each epoch, including the kurtosis [63], skewness [64], line length, 1st Quartile (Q1), and 3rd Quartile (Q3), as defined in Table 1. The time domain features and their sizes are shown in Table 2.

3.1.2. Frequency domain features

We extract EEG frequency features using FFT to obtain the energy at various frequencies. Then we denote each channel as a node and calculate the correlation coefficient matrix of the frequency energy between any two channels. Finally, the eigenvalues of correlation coefficient matrix are used as features in the frequency domain. The frequency domain features and their sizes are listed in Table 2.

Table 2
Features of 20 channels EEG.

Type	Feature	Size
Time	kurtosis, skewness, line length, 1*st* quartile, 3*rd* quartile	20 × 5
Frequency	amplitude in frequency (1–48 Hz)	20 × 48
Frequency	correlation matrix (upper triangular)	190
Frequency	eigenvalues of correlation matrix between 20 channels	20
Net (time)	time PMNet matrix (upper triangular)	190
Net (time)	eigenvalues of time PMNet matrix between 20 channels	20
Net (time)	AD, CC, CPL, MD of time PMNet	5
Net (frequency)	frequency PMNet (upper triangular)	190
Net (frequency)	eigenvalues of frequency PMNet matrix	20
Net (frequency)	AD, CC, CPL, MD of frequency PMNet	5

3.1.3. Features of PMNet

The functional brain network shows small-world characteristics, and the network structure exhibit synchronization phenomena during epileptic seizures [56]. Therefore, it is a complex network with a multi-scale and hierarchical structure [65,66]. This paper proposes a method for constructing PMNet combining PCC and MI between each pair of EEG channels. The time domain and frequency domain of EEG signals are used to build PMNet (PCC-MI combined) network separately. The network features are extracted from these brain networks and used in seizure detection. The process of building the time domain or frequency domain PMNet is shown in Fig. 2.

(1) Construction of brain PMNet based on time domain EEG

Use a Butterworth filter on each epoch to remove low-frequency and high-frequency noise. After that, calculate the PCC matrix and the MI matrix on the 20-channel EEG signals, respectively, as following Eqs. (1) and (2). Then we can get two networks as PCCNet and MINet.

$$PCC(X,Y) = \left| \frac{\sum_{i=0}^{n}(x_i - \bar{x})(y_i - \bar{y})}{[\sum_{i=0}^{n}(x_i - \bar{x})^2 \sum_{i=0}^{n}(y_i - \bar{y})^2]^{1/2}} \right|, \tag{1}$$

$$\begin{aligned} MI(X,Y) &= H(X) + H(Y) - H(X,Y) \\ &= -\sum_{i=0}^{n} p(x_i)\ln p(x_i) - \sum_{j=0}^{n} p(y_j)\ln p(y_j) \\ &\quad + \sum_{i=0}^{n}\sum_{j=0}^{n} p(x_i,y_j)\ln p(x_i,y_j). \end{aligned} \tag{2}$$

where $X = (x_0, x_1, \ldots, x_n)$ and $Y = (y_0, y_1, \ldots, y_n)$ respectively represent two EEG channels with the same length of n in an epoch. This article only considers the strength of correlation between arbitrary pair of two channels, and only uses the absolute value of PCC and MI. When calculating the MI matrix, use the EEG to construct a histogram with Freedman Diaconis Estimator, calculate the probability of each bar, and get MI.

Finally, normalize the PCC matrix and MI matrix for each epoch, obtain the PMNet matrix with Hadamard product as PMNet = PCC ⊙ MI, and get a network of PMNet. When calculating PMNet, using dot multiplication instead of weighting is because the weight is difficult to predict. The addition operation in the weighting will cause the amplification of specific properties, thereby ignoring the influence of the comprehensive properties.

(2) Construction of brain PMNet based on frequency domain EEG

The time-domain-based brain PMNet only considers the voltage amplitude changes of the EEG signal, and lacks frequency information. Therefore, we obtain the frequency-domain-based brain PMNet by adding FFT before getting PCC and MI networks, as shown in Fig. 2.

(3) Extract structure features of networks

Average degree (AD): Each channel is regarded as a node in the functional brain network from time or frequency domain EEG data. In the PMNet, the connection strength between node u and node v is a_{uv}. Then, the degree of node u is defined as the number of nodes associated with node u:

$$k_u = \sum_{v \in N} a_{uv}, \tag{3}$$

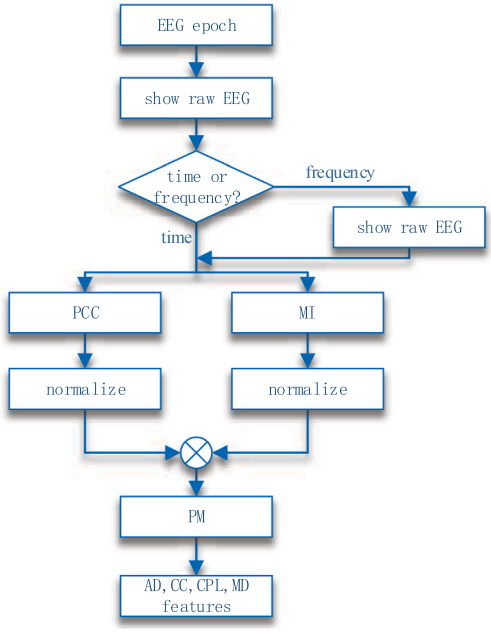


Fig. 2. The process of constructing a brain PMNet based on time or frequency domain.

where N is the set of all nodes, and in our application, we have $N = 20$ nodes (channels). The AD of the network is

$$AD = \langle K \rangle = \sum_{u \in N} k_u. \tag{4}$$

Clustering coefficient (CC): CC measures of the abundance of connected triangles in a network. The CC of the network [67] is defined as

$$CC = \frac{1}{N}\sum_{u \in N} CC_u = \frac{1}{N}\sum_{u \in N} \frac{2t_u}{k_u(k_u - 1)}, \tag{5}$$

where n is the number of nodes in set N, CC_u is the clustering coefficient of node u, t_u is the number of triangles linked to node u.

Characteristic path length (CPL): The CPL of node u is the average shortest path length d_{uv} between it and any other node v. The average CPL of the network [68] is defined as

$$CPL = \frac{1}{N}\sum_{u \in N} L_u = \frac{1}{N}\sum_{u \in N} \frac{\sum_{v \in N, v \neq u} d_{uv}}{N - 1}. \tag{6}$$

Modularity (MD): MD is an indicator of the quality of community in the network. Usually, the epileptic area is often a specific region in the brain. The community mode of seizure is different from other regions during the seizure [69]. Therefore, MD is a feasible measure of the structure of brain networks. The definition of MD [68] is

$$MD = \sum_{u \in M}(e_{uu} - (\sum_{v \in M} e_{uv})^2), \tag{7}$$

Algorithm 1 Pseudo code of the PMNet construction and network structure feature extraction

Input: 20 channel data in an epoch, length n, channel number N
Output: AD, CC, CPL, MD of time or frequency domain networks

// Build a PMNet
for EEG data of arbitrary two channels in an epoch **do**
  if time-domain network **then**
    pick data of two channels as X, Y;
  else
    pick data of two channels;
    fast Fourier Transform of two channel data;
    the spectral data for two channels X, Y;
for EEG data of arbitrary two channels in an epoch **do**
  calculate the PCC of X and Y;
get a 20×20 matrix of PCC with Eq. (1);
normalize the matrix of PCC;
for EEG data of arbitrary two channels in an epoch **do**
  Statistics on the probability distribution of channel X and Y;
  calculate the MI of X and Y with Eq. (2);
get a 20×20 matrix of MI;
normalize the matrix of MI;
calculate $PMNet = PCC \odot MI$;
// Calculate the features of AD, CC, CPL, MD
for each item (channel) in 20×20 matrix of PM **do**
  calculate the degree k_u with Eq. (3) , CC_u with Eq. (5), L_u with Eq. (6), e_{uv} with Eq. (7);
calculate the AD with Eq. (4), CC_u with Eq. (5), CPL with Eq. (6), MD with Eq. (7);

where M is the set of non-overlapping modules in the network, and e_{uv} is the proportion of all links that connect nodes in module u with nodes in module v.

Based on the method proposed in Section 3, we construct time-domain brain networks from each time domain epoch, and calculate the AD, CC, CPL and MD, as shown in Fig. 3. Moreover, Fig. 4 shows these relevant parameters of the frequency domain brain networks. Figs. 3 and 4 show that the seizure period is on the epochs **[1015, 1066]** , and the other epochs are the non-seizure period. It can be seen that there are significant differences between seizures and non-seizures in time and frequency domain characteristics. For example, in the seizures period in Fig. 4, the frequency domain MD has a higher value. However, we also found that in the non-seizure period around epoch **[1250]** , the value of MD is also tremendous, which is prone to misjudgment. Therefore, the brain network structure characters can be used as an essential feature of seizure detection. Still, more time and frequency domain parameters without network structures are also needed to improve the effect.

Algorithm 1 represents the pseudo-code of the PMNet construction and network structure feature extraction.

3.2. Feature dimensionality reduction using PCA

PCA is a standard feature dimensionality reduction method [70]. PCA can search a hyperplane in the orthogonal space closest to the data and meets the maximum separability on this hyperplane. PCA is essentially a method of maximizing the variance, mapping the sample data to an orthogonal space to reduce the feature vector dimension and maximize the practical information as much as possible. The specific solution steps are as follows:

- Normalize all sample data $X = (x_1, x_2, \ldots, x_n)$ with $x_i = x_i - \frac{1}{n}\sum_{i=1}^{n} x_i$, then calculate the covariance matrix XX^T.
- Decompose the eigenvalues of the covariance matrix with $XX^T\omega_i = \omega_i\lambda_i$, sort the eigenvalues in descending order, and then construct a hyperplane $W = (\omega_1, \omega_2, \ldots, \omega_d)$ corresponding to the most significant d eigenvalues.
- Calculate the proportion of principal components. The weight of each eigenvalue indicates the amount of information the data can provide on its eigenvector. The weight threshold in our application is set to 0.95 to obtain a smaller value of d, as follows

$$\frac{\sum_{i=1}^{d}\lambda_i}{\sum_{i=t}^{d}} \geq 95\% \tag{8}$$

3.3. Support vector machine

Seizure detection is usually a binary classification problem resulting from seizure or non-seizure. SVM is a widely used supervised classification algorithm. It is essential to find an optimal hyperplane to separate two types of samples from limited sample information to improve generalization ability. The EEG signal is a random non-stationary signal. Therefore, the features extracted from the seizure and non-seizure data are not linearly separable. The kernel function can map the feature samples to a suitable feature space. In this paper, we use SVM to classify the multi-domain features of EEG and detect seizures. This paper uses the RBF kernel function to obtain a better classification performance [71].

4. Experiment results and discussion

4.1. Data preparation

The EEG datasets used in this paper are the CHB-MIT Scalp EEG dataset [72] and the SIENA dataset [73].

The CHB-MIT dataset includes 23 patient cases, of which 5 males (3–22 years old), 17 females (1.5–19 years old), and one case with unknown gender and age. This dataset contains 969 hours of recordings with 173 seizures (clonic, atonic, tonic). All EEG data are sampled at 256 Hz frequency and 16-bit resolution. Most cases contain 23 EEG channel signals, and the EEG electrode positions refer to the international 10–20 system. Each case in the dataset contains 9–42 continuous *.edf files. Considering that the EEG signal is mixed with interference from eye movements, we remove the data of electrodes FP1 and FP2. Since the left ear electrode is sometimes affected by electrocardiogram (EKG), we also remove the signal from electrodes FT9 and FT10 near the ears to maintain the symmetry of the signal.

The SIENA dataset contains scalp EEG data from 14 patients, including 9 males (36–71 years old) and 5 females (20–58 years old). This dataset consists of 128 hours of recordings with 47 seizures. Most of these cases have focal onset impaired awareness (IAS), and each patient case contains 1 to 5 EEG recording files in *.edf format. All records are sampled at a frequency of 512 Hz with the International 10–20 system. A total of 46 epileptic seizures were recorded in this dataset. In this paper, the same preprocessing method applied to the CHB-MIT dataset is used for this dataset.

The samples of seizure and non-seizure in datasets are imbalanced in these datasets. The non-seizure samples are much more than seizure samples. Therefore, we adopt the method of random undersampling for the non-seizure data, so that there is the same scale between seizure and non-seizure sample data. As Fig. 5 shows, under the scheme of cutting EEG into 1-second and 50% overlap epochs, a total number of n_0 positive samples can be obtained. Because the non-seizure duration is much longer than the seizure duration, n_0 epochs are randomly selected from the non-seizure duration to form a negative sample set. After obtaining the balanced and enhanced sample set, we randomly choose $n_e = n_0 \times 20\%$ of the epochs from the sample set as the test set, where n_e indicates the number of positive or negative epochs in the

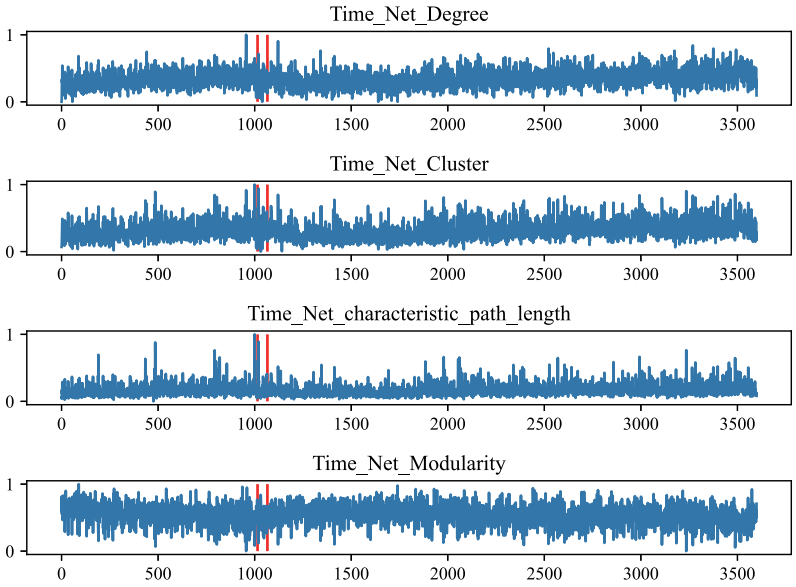


Fig. 3. Brain network characters change in the time domain (epoch = 1 s).

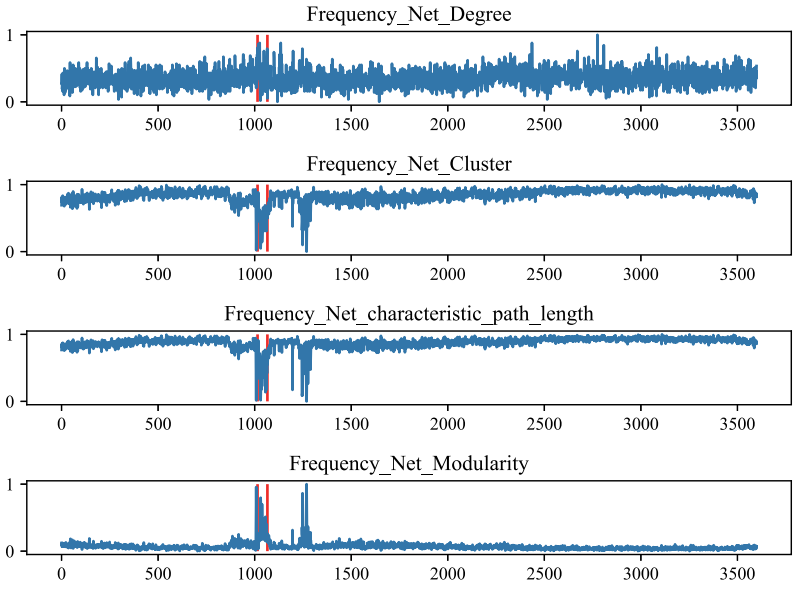


Fig. 4. Brain network characters change in the frequency domain (epoch = 1 s).

test set. Then use the BootStrap to divide the rest $n_t + n_v = n_0 \times 80\%$ epochs into training or testing sets, where n_t and n_v indicates the number of positive or negative epochs in the training set and validation set, separately. Compared with the Holdout resampling method, the BootStrap randomly divides a fixed proportion, and the experimental results obtained are closer to the ideal model. While compared with the cross-validation method such as the Leave-p-out, the BootStrap saves a lot of time overhead. With BootStrap, the ratio of training set to validation set is about $n_t/n_v = 1 - e^{-1}/e^{-1} \approx 1.72$ [74]. Model performances are reported on the test set.

The experimental results in this paper are all the average of the results of 100 times. The experiment uses Python 3.7 with Scikit-Learn, Scipy, and Numpy on a computer with the following configuration: Intel(R) Core(TM) i7-8750H @2.20 GHz CPU processor, 16 GB RAM.

4.2. Evaluation criteria

In order to evaluate the generalization ability of the model trained by the proposed methods, the confusion matrix is shown in Table 3.

Table 3
Confusion matrix of seizure detection.

	Predicted seizure	Predicted non-seizure
Actual seizure	TP	FN
Actual non-seizure	FP	TN

Based on the confusion matrix, the statistical indicators of accuracy (AC), sensitivity (SE), and specificity (SP) can be used in this two-classification problem.

The AC refers to the proportion of data that is correctly identified as seizures and non-seizure samples in all epochs. The equation of AC is as follows:

$$\mathrm{AC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \times 100\% \tag{9}$$

The SE refers to the proportion of correctly identified seizure samples in the total actual seizure epochs. The equation of SE is as follows:

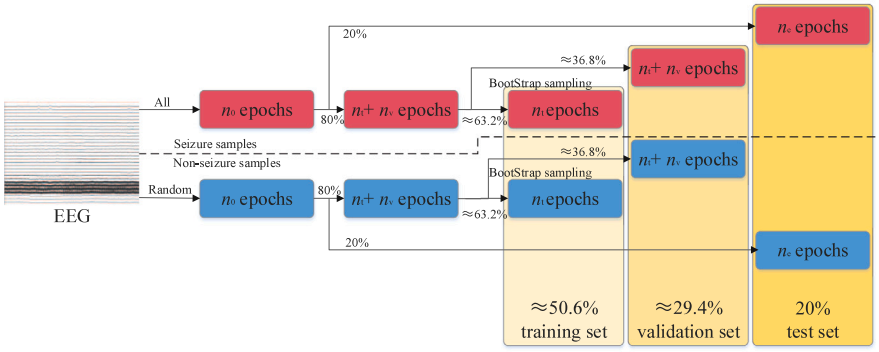
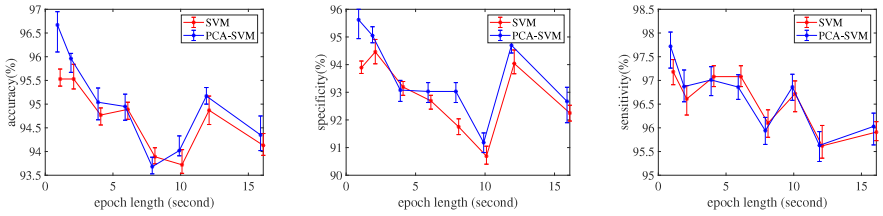


Fig. 5. Demonstration of dataset partition.



(a) AC (b) SP (c) SE

Fig. 6. Performance comparison between PCA-SVM and SVM with various epochs on CHB-MIT dataset. Note: In order to display the error bar clearly, the ordinate values of epoch for PCA-SVM and SVM are staggered arrangement.

$$\mathrm{SE} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \times 100\% \tag{10}$$

The SP refers to the proportion of correctly identified non-seizures in the total number of actual non-seizures epochs. The equation of SP is as follows:

$$\mathrm{SP} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}} \times 100\% \tag{11}$$

4.3. Results

4.3.1. The influence of epoch length and PCA

Furthermore, this paper analyzes the impacts of different scales of epoch sizes and PCA on the performance of the proposed method. Fig. 6 shows the performance of different classifiers on various epochs. As shown in Fig. 6, it can be observed that SVM and PCA-SVM have better performance on AC, SP, and SE indicators. Fig. 7 shows the training time of different classifiers under various scales of epochs. We can find out that SVM takes much longer than PCA-SVM. The results of AC, SP, and SE using PCA-SVM are generally better than SVM, and the training time is significantly reduced. Therefore, SVM essentially finds the best hyperplane in the feature space, and PCA happens to make redundant high-dimensional features. The space is changed to a more refined low-dimensional feature space. The PCA helps SVM accelerate the gradient iteration in the training process and slightly improves the final performance of SVM.

4.3.2. Ablation experiment of features

Table 4 shows the AC, SP, and SE results obtained by applying classifiers of PCA-SVM on the CHB-MIT and SIENA datasets with epochs = 1 s. After adding PCCNet (time, frequency and PCCNet) or MINet (time, frequency and MINet) features, respectively. The recognition rates of seizure samples and non-seizure samples (SE and SP) are improved with SVM. After adding PMNet (time, frequency and PMNet) features, compared with the traditional Time-Freq method, the AC increases by about 3.25%, the SP increases by about 4.24%, and the SE increases by about 2.25% on the CHB-MIT. While AC increases by about 5.33%,

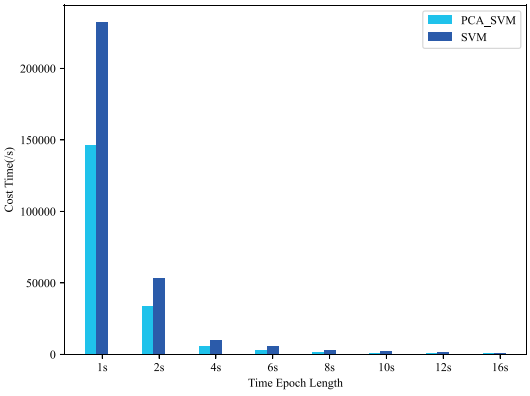


Fig. 7. Training time for different classifiers on various epochs (CHB-MIT).

the SP increases by about 5.61%, and the SE increases by about 5.05% on the SIENA. Therefore, using Time-Freq-PMNet features and the PCA-SVM classifier proposed in this paper can effectively improve the classifier's ability to detect seizures. The Wilcoxon signed-rank test is used to evaluate the significant difference between the feature selection strategies, as shown in Table 5. If the two feature selection strategies are considered significantly different while the p-value < 0.05. This result shows that PCA-SVM with PMNet has a statistical significance against the other Time-Freq-PMNet, PCCNet or MINet feature selection strategies.

4.3.3. Comparison with other methods

In this part, we compare the evaluation indicators of seizure detection with the results of other methods. The comparison results are carried out on the CHB-MIT and SIENA datasets. In our investigations with EEG technicians (reading EEG records and manually labeling seizures for neurologists), we find that the rapid labeling of seizures has practical application value in a long time EEG record, reducing the EEG technician's work intensity. In the rapid labeling by machine learning,

Table 4
Performance comparison in different net features on CHB-MIT and SIENA (average value: .av, standard deviation: .sd).

Classifier	Feature	Dataset	AC.av (%)	AC.sd	SP.av (%)	SP.sd	SE.av (%)	SE.sd
PCA-SVM	Time	CHB-MIT	83.36	0.0038	81.45	0.0033	85.28	0.0054
PCA-SVM	Freq	CHB-MIT	90.04	0.0023	88.35	0.0047	91.75	0.0030
PCA-SVM	Time-Freq	CHB-MIT	93.42	0.0039	91.38	0.0084	95.47	0.0029
PCA-SVM	Time-Freq-PCCNet	CHB-MIT	94.66	0.0027	93.17	0.0042	96.16	0.0034
PCA-SVM	Time-Freq-MINet	CHB-MIT	95.21	0.0021	93.68	0.0023	96.75	0.0037
PCA-SVM	Time-Freq-PMNet	CHB-MIT	**96.67**	0.0027	**95.62**	0.0032	**97.72**	0.0026
PCA-SVM	Time	SIENA	82.04	0.0027	81.63	0.0053	82.46	0.0045
PCA-SVM	Freq	SIENA	86.60	0.0032	85.79	0.0045	87.43	0.0051
PCA-SVM	Time-Freq	SIENA	90.35	0.0043	88.29	0.0052	92.46	0.0053
PCA-SVM	Time-Freq-PCCNet	SIENA	93.01	0.0037	91.87	0.0044	94.17	0.0043
PCA-SVM	Time-Freq-MINet	SIENA	94.60	0.0030	93.12	0.0046	96.12	0.0031
PCA-SVM	Time-Freq-PMNet	SIENA	**95.68**	0.0046	**93.90**	0.0070	**97.51**	0.0039

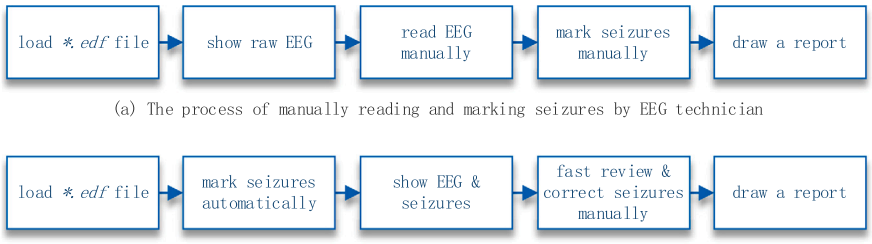


Fig. 8. Comparison of manual or automatic algorithm marking seizure business processes.

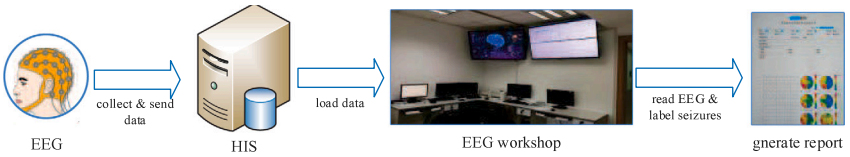


Fig. 9. Schematic of the proposed system.

Table 5
The Wilcoxon sign-rank test between features of Time-Freq-PMNet and other features on CHB-MIT and SIENA.

Classifier	Time-Freq-PMNet vs.	Dataset	AC *p*-value	SP *p*-value	SE *p*-value
PCA-SVM	Time	CHB-MIT	1.83e−04	1.83e−04	1.81e−0
PCA-SVM	Freq	CHB-MIT	1.83e−04	1.83e−04	1.82e−04
PCA-SVM	Time-Freq	CHB-MIT	1.82e−04	1.81e−04	1.82e−04
PCA-SVM	Time-Freq-PCCNet	CHB-MIT	1.79e−04	1.83e−04	1.82e−04
PCA-SVM	Time-Freq-MINet	CHB-MIT	1.83e−04	1.83e−04	3.28e−04
PCA-SVM	Time	SIENA	1.82e−04	1.79e−04	1.81e−04
PCA-SVM	Freq	SIENA	1.82e−04	1.79e−04	1.81e−04
PCA-SVM	Time-Freq	SIENA	1.81e−04	1.76e−04	1.79e−04
PCA-SVM	Time-Freq-PCCNet	SIENA	1.76e−04	1.78e−04	2.41e−04
PCA-SVM	Time-Freq-MINet	SIENA	1.81e−04	1.75e−04	1.75e−04

even if the label of seizure is wrong, the EEG technician can manually correct it, as shown in the comparison of Fig. 8. Therefore, the SE can more accurately indicate the degree of missed detection in AC, SP, and SE. We improve the EEG reading and marking system in the cooperative hospital to reduce the work intensity and improve the work efficiency of EEG technicians. The schematic of the proposed system is shown in Fig. 9.

As shown in Table 6, the average performance of SE based on the PCA-SVM proposed in this paper on both CHB-MIT and SIENA datasets is higher than that of previous other studies. However, AC and SP in Wu's paper [77] are much higher than the method proposed in this article.

4.3.4. Verify the effectiveness of the method on actual clinical data

West syndrome (WS), also known as infantile spasms, is an epileptic seizure disorder in babies. WS is first described in 1841. It usually begins in the first year, peaks between 4 and 7 months, and goes away by age 4. Nevertheless, many children have other types of epilepsy later in their lives. WS presents epileptic spasms, and the patients' EEG has peak rhythm disorder characteristics [82,83]. The EEG dataset used in this section is WS patient data from the Children's Hospital, Zhejiang University School of Medicine. The dataset includes 13 valid cases of children, but the age and gender are unclear. This dataset consists of 59 hours of recordings with 103 min of seizure duration. All records are sampled at a frequency of 1000 Hz. The recording files of *.edf contain 21 EEG channels with the international 10–20 system. The sample enhancement and preprocessing methods are similar to those on CHB-MIT and SIENA datasets.

We train and test the effectiveness of PCA-SVM method on the WS dataset. Table 7 shows the demographic information of the WS dataset. Table 8 shows the patient-by-patient results of PCA-SVM method with WS dataset. Table 9 compares the performance between our method and Wu's method [77] on WS. The result confirms that the PCA-SVM using PMNet features achieves the optimal value at AC = 95.82%, SP = 94.89%, and SE = 96.76% on the real dataset of WS. This result shows that the proposed method has good generalization performance. (See Table 8.)

4.4. Discussion

This study introduces a model with functional brain network structure features to predict seizure. Brain structure usually shows regional

Table 6
Performance comparison with other methods.

Method	Dataset	Patients	Seizure number	Duration	
Janjarasjitt et al. (2017) [75]	CHB-MIT	23	173	969 h	
Raghu et al. (2019) [76]	CHB-MIT	23	173	969 h	
Wu DP et al. (2019) [77]	CHB-MIT	23	173	969 h	
Wang ZY et al. (2021) [78]	CHB-MIT	23	173	969 h	
Usman et al. (2021) [79]	CHBMIT	23	173	969 h	
Detti et al. (2018) [80]	SIENA	9	47	128 h	
Dissanayake et al. (2021) [81]	SIENA	9	47	128 h	
Our method (CHB-MIT)	CHB-MIT	23	173	969 h	
Our method (SIENA)	SIENA	9	47	128 h	
Method	Feature	Classifier	AC (%)	SP (%)	SE (%)
Janjarasjitt et al. (2017) [75]	linelength, NE, variance, average power, max	SVM	95.17	66.35	96.91
Raghu et al. (2019) [76]	spectral, DWT, entropy	SVM	94.38	94.55	94.21
Wu DP et al. (2019) [77]	time, freq, time-freq, aEEG	RF	**99.36**	**99.41**	82.98
Wang ZY et al. (2021) [78]	feature extracted from CNN	CNN	80.5	85.8	75.1
Usman et al. (2021) [79]	feature extracted from CNN	LSTM	92.75	92.50	93.00
Detti et al. (2018) [80]	MAACD and graph theory features	SVM	96.76	97.81	95.71
Dissanayake et al. (2021) [81]	Mel-frequency cepstrum coefficients (MFCCs)	C-GNN	96.05	96.61	96.05
Our method (CHB-MIT)	time, freq, network features	PCA-SVM	96.67	95.62	**97.72**
Our method (SIENA)	time, freq, network features	PCA-SVM	95.68	93.90	**97.51**

Table 7
Demographic information of the WS dataset.

ID	Gender	Age	Drug utilization	Total duration	Seizure duration
WS1	F	4 months + 18 days	None	47468 s	331.5 s
WS2	F	1 year	None	7103 s	278.5 s
WS3	M	6 months + 23 days	None	53067 s	873.3 s
WS4	M	9 months + 12 days	None	5188 s	305.4 s
WS5	M	4 months + 9 days	None	6462 s	274.0 s
WS6	M	7 months + 23 days	None	7421 s	407.9 s
WS7	M	1 year	None	7184 s	639.0 s
WS8	M	5 months + 4 days	None	9416 s	803.2 s
WS9	M	6 months + 4 days	None	17698 s	958.0 s
WS10	F	6 months + 25 days	None	9001 s	203.3 s
WS11	M	6 months + 7 days	None	20383 s	434.2 s
WS12	F	1 year + 6 month	None	7823 s	387.3 s
WS13	M	1 year + 5 month	None	14492 s	318.1 s
Overall	–	–	–	212706 s	6213.7 s

Table 8
Patient-by-patient results of WS (average value: .av, standard deviation: .sd).

ID	AC.av (%)	AC.sd	SP.av (%)	SP.sd	SE.av (%)	SE.sd
WS1	96.36	0.0102	96.20	0.0114	96.52	0.0100
WS2	93.99	0.0093	89.50	0.0162	98.55	0.0076
WS3	94.61	0.0075	95.13	0.0130	94.10	0.0063
WS4	94.01	0.0127	93.53	0.0095	94.50	0.0219
WS5	94.34	0.0104	94.01	0.0191	94.67	0.0167
WS6	96.92	0.0089	95.98	0.0128	97.87	0.0134
WS7	97.51	0.0069	97.34	0.0080	97.67	0.0073
WS8	97.47	0.0041	96.84	0.0032	98.10	0.0087
WS9	94.97	0.0075	92.87	0.0091	97.10	0.0083
WS10	92.77	0.0119	89.61	0.0192	96.00	0.0105
WS11	97.58	0.0045	97.75	0.0088	97.41	0.0066
WS12	90.41	0.0109	85.89	0.0133	95.00	0.0131
WS13	98.71	0.0048	98.50	0.0053	98.92	0.0067
Overall	95.82	0.0034	94.89	0.0047	96.76	0.0039

and interrelated characteristics, and the patterns in or between the regions are different. Therefore, we can fully use these characteristics of brain networks and extract the structural features of the functional brain network of EEG using the complex network theory (graph theory) to detect the seizure. This is what this manuscript is trying to explore. Since EEG is a time series signal, and its distribution in energy in the different bands of frequency is also meaningful for seizures, this paper does not intend to remove the time domain and frequency domain features. However, it attempts to add network structure features of functional brain networks to the time domain and frequency domain features to expand the research.

As demonstrated in the previous results of Tables 4 and 5 in the ablation experiment, take the results with Time-Freq features as a baseline, and PCCNet, MINet, and PMNet features can significantly improve the detection performance. This result is basically consistent with the trend of other similar studies by using complex network theory [44]. In order to explore the impact of various variables on the results, in Section 4.3.1 we explore the influence of epoch length and PCA. The comprehensive effect of seizure detection is the best with the epochs = 1 s than other epoch lengths. In the design of the classifier, we choose a relatively simple SVM, hoping to have broader application potential. Based on SVM, we add the PCA dimension reduction module. The results show that dimensionality reduction is beneficial in improving the speed and performance of the classifier.

In addition to testing on open datasets of CHB-MIT and SIENA, we also tested on the private dataset from children's hospital. The test results show that our method has relatively consistent results on these three datasets, and all of their performances are acceptable. Due to the high score of SE, we will further develop a tool or APP to automatically detect seizures and reduce the workload of EEG technicians with advice from doctors.

Table 9
Performance comparison with Wu DP's method [77] of the WS dataset.

Method	Dataset	AC.av (%)	AC.sd	SP.av (%)	SP.sd	SE.av (%)	SE.sd
Wu DP et al. (2019) [77]	WS	91.62	0.0041	96.76	0.0038	86.42	0.0077
Our method	WS	95.82	0.0034	94.89	0.0047	96.76	0.0039

5. Conclusion

5.1. Summary

This paper constructs an epileptic seizure detection method with time and frequency functional brain networks and multi-domain features. The main contributions of this paper are constructing the functional brain network PMNet and extracting the network structure features for seizure detection. This paper builds time and frequency functional brain networks according to the PCC and MI between each pair of EEG signal channels to form functional brain networks of PMNet, and then uses the AD, CC, CPL, and MD metrics to calculate the structure features of PMNet. After using PCA for dimensionality reduction and SVM for seizure classification, the AC, SP, and SE are 96.67%, 95.62%, 97.72% on the CHB-MIT dataset, and are 95.68%, 93.90%, 97.51% on the SIENA dataset, respectively. Furthermore, applying PCA-SVM with PMNet in the real WS dataset can achieve AC = 95.82%, SP= 94.89%, and SE = 96.76%. The performance of SP and AC still need to be improved in our future work. In hospital applications, algorithms for detecting epileptic seizures can effectively reduce the workload of EEG technicians. Therefore, in this work scenario, the indicator of SE is essential. The results demonstrate that our method based on brain PMNet and other multi-domain EEG features performs better seizure detection on SE. Our method is deployed with a simple automatic seizure detection system in hospital applications, which can reduce the workload of EEG technicians in reading EEG and marking seizures.

5.2. Future work

The literature shows that the brain function network presents a synchronous phenomenon during seizures. Therefore, in our future work, we can consider further introducing phase locking value and other methods to build a brain function network combined with timing, frequency, energy, and phase information. The structural measurement metrics of the brain function network include regional, medium, and global scale parameters. In this paper, regional and global scale parameters are considered. But the dynamical working mode of the brain network contains locally, medium, and global scales. Therefore, future research can also carries out an in-depth exploration of the network structure evaluation metrics.

CRediT authorship contribution statement

Lurong Jiang: Conceptualization, Methodology, Writing. **Jiawang He:** Writing – original draft. **Hangyi Pan:** Software. **Duanpo Wu:** Methodology, Writing – review & editing. **Tiejia Jiang:** Resources. **Junbiao Liu:** Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Ethical standards

This research has been approved by Ethic Committee of the Children's Hospital, Zhejiang University School of Medicine (2019-IRB-152).

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