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FFT-based deep feature learning method for EEG classification

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A R T I C L E I N F O

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A B S T R A C T

This study introduces a new method for electroencephalogram (EEG) signal classification based on deep learning model, by which relevant features are automatically learned in a supervised learning framework. The fast Fourier transform (FFT) has been applied in a novel way to generate the EEG matrix. And a PCA neural network (PCANet) is designed to learn the hidden information from the frequency matrix of EEG signals. And these deep features are then given as inputs to train a support vector machine (SVM) for recognition of epileptic seizures. The experiments are carried out with two authoritative databases provided by the Bonn University (Database A) and Children's Hospital in Boston (Database B), relatively. Additionally, we have evaluated the influence of all parameters for the proposed scheme to obtain the optimal model with better generalization and expansibility. The proposed feature learning method concerned in this work is proved very useful to distinguish seizure events from both short and long EEG recordings. Experimental results obtained by analyzing Database A are not less than 99% accuracy in seven problems. The effectiveness is also verified on Database B with an average accuracy of 98.47% across 23 patients. Our FFT-based PCANet not only achieves the satisfied results, but also exhibits better stability across different classification cases or patients, which indicates the worth in practical applications for diagnostic reference in clinics.

1. Introduction

Electroencephalogram (EEG) is the spontaneous electrical activity recording of cerebral cortex nerve cells, which carries a large amount of physiology and pathology information [1]. The measurement of salient features in EEG signals is an objective method for the evaluation of brain state and function. Therefore, EEG is deemed as the gold standard for the diagnosis of brain abnormalities, especially epilepsy [2,3]. Epilepsy is a neurological disorder caused by excessive synchronization of neuronal discharges [4]. The traditional method by visual monitoring of the long-term EEG recording is a very subjective and time-consuming process. An efficient algorithm that detects the seizures automatically and accurately would benefit neurologists in releasing their workloads and providing timely intervention for patients.

Growing attention has recently been given to the auxiliary detection of epilepsy. Many researchers have put more efforts on extracting pertinent features from epileptic EEG signals. Li et al. [5] have studied the ability of fuzzy entropy (FuzzyEn) and distribution entropy (DistEn) to tracks the dynamics of brain activity. The results have shown that the two features may complement each other and play a more positive and constructive role in achieving the best performance. Fu et al. [6] transformed the EEG into time-frequency image by Hilbert-Huang transform and extracted mean, variance, skewness and kurtosis of pixel intensity as features. In literature [7], a hybrid method using the combined empirical mode decomposition (EMD) and discrete wavelet transform (DWT) was proposed for seizure detection. Subsequently, the authors calculated three entropy-based features in the EMD-DWT domain with the primary goal of characterizing focal and non-focal EEG signals. Zhang et al. [8] extracted some temporal and non-linear features from a series of product functions obtained by local mean decomposition (LMD). Then five different classifiers were utilized to perform seizure detection based on the extracted features. Makaram et al. [9] developed an algorithm that utilized four time-domain features and eight multi-scale entropy features to discriminate five seizure onset patterns from intracerebral EEG signals. A seizure classification method by applying tunable-Q wavelet transform (TQWT) was reported in the work of Bhattacharyya et al. [10], where the multivariate fuzzy entropy (mvFE) was measured from each TQWT sub-band as a decisive feature. In another research, Nishad et al. [11] has exploited the TQWT approach to diagnose epileptic seizures. In [12], a methodology with a difference was presented to discriminate seizure signals from normal ones. The authors applied the autoencoder (AE) error to automatically detect

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seizures in a patient-specific manner without requiring seizure data in training. Shoeibi et al. [13] used a convolutional AE for automatic feature learning and compared the obtained results with the classic methods. It should be found that most of the existing approaches rely on suggesting appropriate hand-crafted features to attain better classification results, which is a repeated process of trial and error based on empirical evidence. Moreover, the characteristics of complexity and subjectivity for the designed features may lead to the tedious procedures and reduced universal applicability. With the aim of overcoming the above problems, deep learning technology has emerged to learn relevant features automatically in a supervised learning framework.

Extracting discerning and unique features is always a crucial procedure in deploying a successful seizure recognition system [14]. Our objective is to design a feature learning algorithm that can automatically learn features from EEG signals with both high accuracy and high generalization. In this regard, we present a promising novel feature extraction model on the basis of principal component analysis network (PCANet) for recognizing the epileptic activity in EEG signal. PCANet is a non-supervised feature extraction method based on the theory of deep learning, which uses PCA to construct the parameters of convolution filters and retains the hierarchical architecture of traditional convolution neural network (CNN). Motivated by the overwhelming success of PCANet over face recognition [15,16], we employ this method to learn and represent both low and high level EEG features. As far we are aware of, researches on the use of PCANet for the processing of EEG signals is somewhat limited. To create a more accurate understanding of EEG, we make a combination of PCANet and fast Fourier transform (FFT) in an innovative way. The proposed FFT-based deep feature learning method consists of three stages: matrix generation, feature learning, and feature classification. The first stage is to reshape a raw EEG signal into a matrix in a view of the frequency domain by FFT. In the second stage, the 2D-PCANet is exploited to automatically learn and discover the features deeply rooted in the generated coefficient matrix to efficiently capture the difference of various EEG types. Finally, a support vector machine (SVM) is performed at the classification process to assign a label for each of the extracted PCANet features. Fig. 1 presents the algorithm architecture proposed in this research. Experiments are carried out with two publicly available databases to test the capacity of this proposed scheme.

The remainder of the article is structured as follows. Section 2 provides the introduction of EEG databases adopted in the study. Section 3 is devoted to the theoretical framework of the proposed method. Continuously, the experimental results are provided in Section4, followed by the conclusions of this work in Section 5.

2. EEG data

Database A: The first database is the open source from Bonn University [17]. This classic database has a total of 500 sequences that are grouped into five sub-sets labeled A, B, C, D and E. Each set contains 100 artifact-free EEG recordings with a sampling rate of 173.17 Hz and 12-bit resolution. Sets A and B are collections of surface EEG segments taken from five healthy volunteers in relaxed and awake state. The signals in the rest of sets were measured from five patients during the pre-surgical evaluation of epilepsy. A description of the database is listed in Table 1. In order to verify the flexibility and universality of this approach, seven different classification tasks that are of great clinical value have been considered in this present research. These combinations, such as A/E, B/E, C/E, D/E, ABCD/E, A/D/E and AB/CD/E are constituted using the above data sets for further investigation.

Database B: The CHB-MIT scalp EEG database [18], which is collected from 23 pediatric subjects with intractable seizures, is the second database adopted in our experiments. Among the patients (18 females and 5 males), the oldest is 22 years old, while the youngest is just 2. And the case “chb24″ is the supplemental data with incomplete information. The data in “chb01″ and “chb21″ are acquired from the same person at different times. For all patients, the bipolar scalp EEG recordings are sampled at 256 Hz using certain common electrodes placed according to the standard international 10−20 system. It should be mentioned that only the EEG records where at least one seizure occurs are considered for analysis. The patient information is presented in Table 2.

3. Proposed algorithm

The proposed algorithm based on FFT and PCANet benefits from the main properties of the deep learning methods, which reveals more effective information embedded in the EEG without depending on hand-engineered features. The methodology is described below.

3.1. Matrix generation using fast Fourier transform

As a means of quantitatively describing the EEG records, the matrix generation is a crucial stage of the proposed framework. The information content in the matrix will influence discrimination ability of the deep features. The classical Fourier transform (FT) analysis can provide excellent description and proper analysis of EEG traces in frequency domain [19]. To reveal such meaningful information from EEG in a

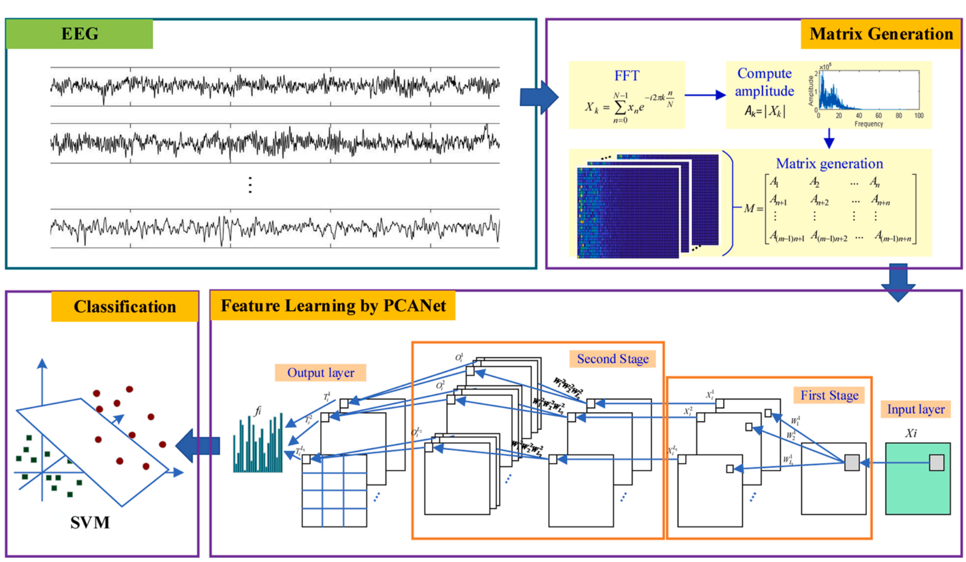

Fig. 1. Flowchart of proposed method.

Table 1
A summary description of Database A.

Data	Set A	Set B	Set C	Set D	Set E
Subject	Five health volunteers		Five epileptic volunteers		
Subjects' state	Awake and eyes open	Awake and eyes closed	Seizure free	Seizure free	Seizure
Electrode placement	International 10−20 system	International 10−20 system	Opposite to epileptogenic zone	Within epileptogenic zone	Within epileptogenic zone
Recording duration	23.6 s	23.6 s	23.6 s	23.6 s	23.6 s
Sample points	4096	4096	4096	4096	4096

Table 2
Detail information of the utilized data.

Patient ID	Gender	Age	No. of seizures	Total duration of seizures (s)	Recording duration (s)
chb01	F	11	7	440	23,920
chb02	M	11	3	172	8156
chb03	F	14	7	400	25,196
chb04	M	22	4	376	38,356
chb05	F	7	5	560	17,996
chb06	F	1.5	10	140	93,212
chb07	F	14.5	3	324	32,532
chb08	M	3.5	5	916	17,996
chb09	F	10	4	276	34,496
chb10	M	3	7	444	50,460
chb11	F	12	3	804	10,056
chb12	F	2	27	988	34,856
chb13	F	3	10	440	25,196
chb14	F	9	8	168	25,196
chb15	M	16	20	1992	50,432
chb16	F	7	8	68	17,996
chb17	F	12	3	292	10,820
chb18	F	18	6	316	20,272
chb19	F	19	3	236	10,544
chb20	F	6	8	292	20,032
chb21	F	13	4	196	13,784
chb22	F	9	3	204	10,796
chb23	F	6	7	424	32,252
chb24	/	/	16	510	23,920

computationally efficient way, a method based on fast Fourier transform (FFT) is adopted to convert a EEG signal into a matrix. The procedures are given below:

Step 1: Obtain the Fourier coefficient for a given signal $x(t)$ in the frequency range [0, 2π] by using the FFT algorithm. The calculation of FT is defined as:

$$F_r = \sum_{u=0}^{M-1} x_n e^{-i2\pi r \frac{u}{M}} \tag{1}$$

where F_r is the FT coefficients, M is the length of input EEG.

Step 2: Calculate the absolute values of thecoefficientsas $A_r=|F_r|$.

Step 3: Transform the A_k into the $m\times n$ matrix form in accordance with sequential arrangement of the sample points. Then the generated matrix X is expressed as

$$X = \begin{bmatrix} A_1\ A_2\ \dots\ A_n \\ A_{n+1}\ A_{n+2}\ \dots\ A_{n+n} \\ \vdots\ \vdots\ \vdots\ \vdots \\ A_{(m-1)n+1}\ A_{(m-1)n+2}\ \dots\ A_{(m-1)n+n} \end{bmatrix}, r = m \times n \tag{2}$$

where m and n is the matrix row and matrix column, respectively.

3.2. Deep feature extraction using PCANet

PCA network (PCANet), which is acknowledged as a simplified deep learning model based on CNN, can progressively learn more abstract and nonlinear relations at a higher level of insight, even with a small amount of training samples. Due to its competitive power for feature learning, PCANet has been successfully used in image processing [20]. In the proposed architecture, PCANet is potentially introduced to extract high-level features from the 2-D data matrix of EEG samples.

Fig. 2 depicts the structure of the PCANet, which mainly comprises three components: cascaded principal component analysis (PCA), binary hashing, and block-wise histograms [21]. Assume that there are N input training EEG matrix of size $m\times n$ after the FFT. For a given sample X_i, a patch with size $k_1\times k_2$ is taken around each point. By subtracting patch mean from each patch, a new matrix is arranged as $\widehat{X}_i = [\widehat{x}_{i,1}, \widehat{x}_{i,2}, \ldots, \widehat{x}_{i,(m-k_1+1)\times(n-k_2+1)}]$, where $\widehat{x}_{i,j}$ denotes the j th mean-removed patch in $\widehat{X}_i$. Then all EEG samples are vectorized and integrated into the following manner [22,23]:

$$\widehat{X} = [\widehat{X}_1, \widehat{X}_2, \ldots \widehat{X}_N] \quad \varepsilon \quad R^{k_1 k_2 \times N_q} \tag{3}$$

where $q=(m\text{-}k_1+1)\times(n\text{-}k_2+1)$. Then, the eigenvectors of $\widehat{X}\widehat{X}^T$ are computed and L_1 principle eigenvectors are selected as PCA filters W_l^1. More specifically

$$W_l^1 = \mathrm{mat}_{k_1 k_2}(q_l(\widehat{X}\widehat{X}^T)) \quad \varepsilon \quad R^{k_1\times k_2}, l = 1, 2, \ldots, L_1 \tag{4}$$

where $q_l(\widehat{X}\widehat{X}^T)$ denotes the l th principle eigenvectors of $\widehat{X}\widehat{X}^T$. And mat (v) is a function that maps the vector $v\ \varepsilon\ R^{k_1\times k_2}$ to a matrix $W\ \varepsilon\ R^{k_1\times k_2}$. Then the output of the l th filter at the first PCA stage is expressed as:

$$Z_i^l = X_i * W_l^1, \quad i = 1, \ldots, N \tag{5}$$

where * represents two-dimensional convolution operator. The similar procedures are repeated on the filter output of the first layer. And the output of the second PCA stage is obtained as:

$$O_i^l = Z_i^l * W_l^2 \quad , i = 1, \ldots, N, l = 1, 2, \ldots, L_2 \tag{6}$$

where L_2 is the number of filters in the second PCA stage. In the final layer, the Heaviside step function is used to to binarize the filtered output of the second PCA stage and the vector of L_2 binary bits can be converted into an integer value by:

$$T_i^l = \sum_{l=1}^{L_2} 2^{l-1} H(Z_i^l * W_l^2), \quad l = 1, 2, \ldots, L_1 \tag{7}$$

where $H(\cdot)$ is a Heaviside step function that sets positive values as 1 and 0 for others. Finally, each of the L_1 components in T_i^l is divided into B blocks. The local histogram of each block is calculated and concatenated into one vector denoted as Bhist(T_i^l). Thus, the PCANet features of the input EEG sample X_i is then defined as:

$$f_i = [\mathrm{Bhist}(T_i^1), \ldots, \mathrm{Bhist}(T_i^{L_1})]^T\ \varepsilon\ R^{(2L_2)L_1 B} \tag{8}$$

The algorithmic performance relies on the choice of parameters including patch size, filter numbers, block sizes and the number of stages. A two-staged PCANet is implemented in our paper since it is proved to be sufficient to learn the higher-level representations of EEG. The other parameters are determined empirically to construct the optimal PCANet model.

3.3. Classification using support vector machine

SVM is a typical supervised machine learning method introduced by

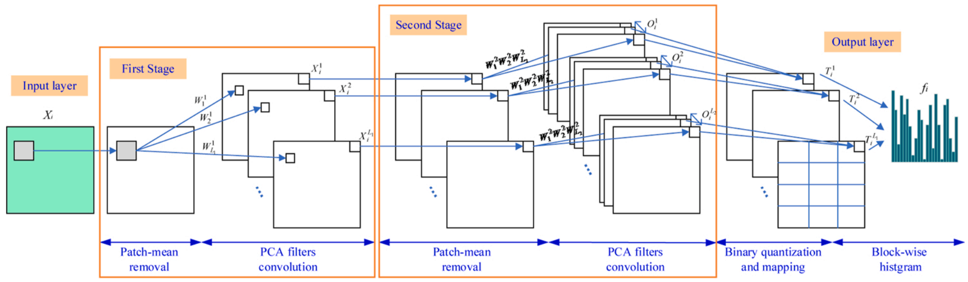

Fig. 2. The structure of the PCANet.

Vapnik in 1992. Based on a solid theoretical basis, SVM has been commonly used across different fields. The basic principle of SVM is to create a separating hyperplane that maximizes the edge of the isolation between the categories with respect to the hyperplane [24]. The specific contents of SVM algorithm can be found in [25,26]. Motivated by literature [27], SVM with radial basis function (RBF) kernel is adopted in this study, where two parameters cost (C) and sigma (σ) are set to 2 and 1 separately.

4. Results and discussion

The designed model is evaluated using two different EEG database mentioned in Section 2. The results of our experiments are presented in terms of four metrics, namely, sensitivity (Sen), specificity (Spe), accuracy (Acc) and area under curve (AUC). The latency of one EEG is computed as well. We use the 10-fold cross validation (CV) to train and test the model.

4.1. Classification performance on database A

To draw reliable conclusions, the database is grouped into seven clinically relevant combinations for exploring a general model. The frequency components of EEG are more useful under the 40 Hz. For the purpose of avoiding unrelated information, the raw EEG signals are band-limited to the desired 0−40 Hz scope by a low pass filter. Then the experiment is carried out by applying our FFT-based feature learning method. The power spectrum of sample EEG and the corresponding matrix plots are shown in Fig. 3. It is observed that the characteristics of EEG signals in the FFT-based matrix plots are significant different for five classes. The better matrix maps from FFT domain will lay a solid foundation for the feature learning of PCANet.

The choice of parameters is of great importance in the construction of our model. Hence, we have explored this model with different parameters, including patch size ($k_1 \times k_2$), filter numbers (L_1, L_2) and block sizes (B). Three experiments are conducted to access the effects of changing parameters on the Acc values of the proposed scheme: **a)** Six different patch sizes corresponding to 5×5, 10×10, 15×15, 20×20, 25×25 and 30×30 are studied respectively, as other parameters are fixed to $L_1 = L_2 = 8$, $B = 25 \times 25$. **b)** Various block sizes (5×5, 10×10, 15×15, 20×20, 25×25 and 30×30) are considered for evaluation with $k_1 = k_2 = 15$ and $L_1 = L_2 = 8$. **c)** The filter numbers ($L_1 = L_2$) are varied from 1 to 10 while $k_1 = k_2 = 15$, $B = 25 \times 25$. We can determine the structure of the model by tuning the three parameters. The results shown in Fig.4 explain that these three parameters have more significant influence on the classification accuracy. Due to the fact that the corresponding Acc values vary within a relatively wide range, the influence of filter numbers on the performance of this method is more remarkable. It is found that the best combination of parameters is $k_1 = k_2 = 15$, $L_1 = L_2 = 8$ and $B = 25 \times 25$ where the classification results of all cases have reached to maximum values. And the optimum parameters of PCANet structure is listed in Table 3.

To analysis the contribution of FFT in the proposed scheme, the performance of PCANet using raw EEG signal is investigated in this paper. The classification results of PCANet using raw EEG signal and FFT based frequency matrix of EEG are shown in Table 4. By using the FFT method, the highest classification performance are found to be 100%, 100%, 100%, 99.0%, 99.60%, 99.33%, and 99.20% of A/E, B/E, C/E, D/E, ABCD/E, A/D/E and AB/CD/E, respectively. To be more rigorous, the Wilcoxon test is performed to assess the statistical significance of the Acc provided in this part. As can be seen from Table 5, there are evident difference between the results of two feature extractors except A/E, since the p-values are less than 0.05. Both methods have yielded 100% of Acc for A/E so the results has no significant difference. The participation of FFT results in an increase in accuracy which is proved to be statistically significance. Such a integration of FFT and PCANet could dramatically improve the classification efficiency. More classification

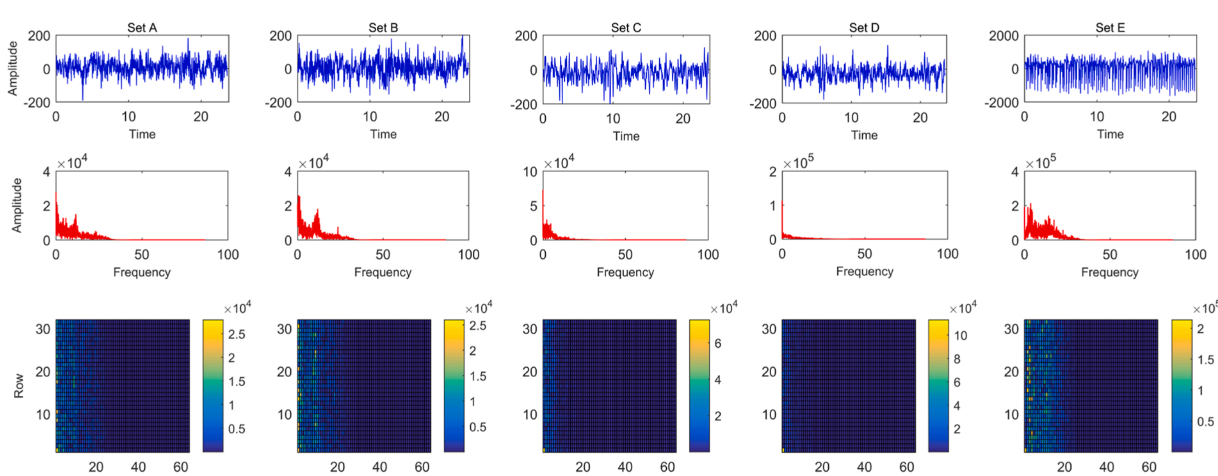

Fig. 3. The power spectrum of sample EEG and the corresponding matrix plots.

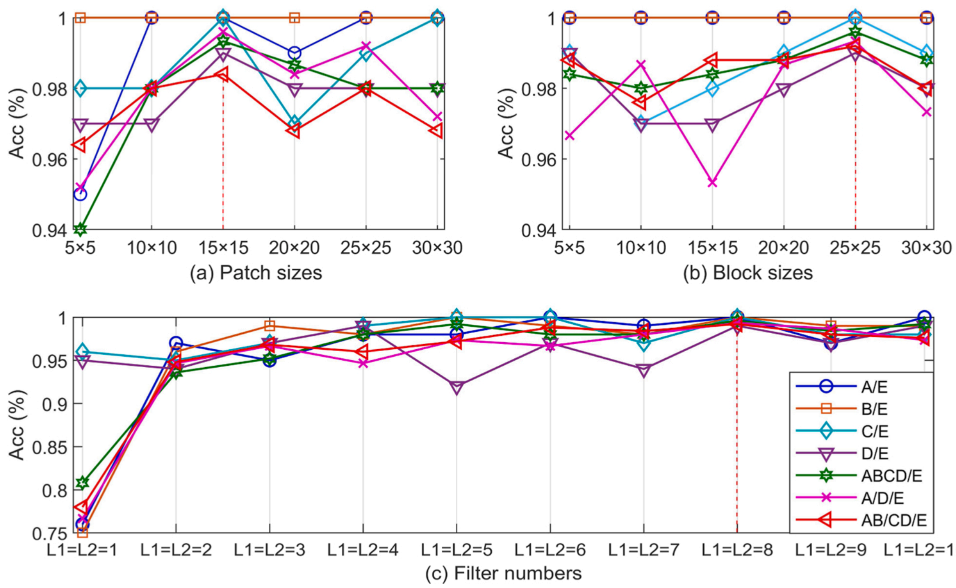

Fig. 4. The variation of accuracy values with different parameters of PCANet. (a) L_1=L_2 = 8 and B = 25 × 25; (b) k_1=k_2 = 15 and B = 25 × 25; (c) k_1=k_2 = 15 and L_1=L_2 = 8.

Table 3
The optimal PCANet parameter values.

Parameter	Value
Input matrix size (m×n)	32 × 64
Patch size (k_1×k_2)	15 × 15
Filter numbers of first layer (L_1)	L_1 = 8
Filter numbers of second layer (L_2)	L_2 = 8
Block size	25 × 25

Table 4
Performance comparison between FFT-PCANet and PCANet.

Cases	FFT-PCANet			PCANet		
	Acc (%)	Spe (%)	Sen (%)	Acc (%)	Spe (%)	Sen (%)
A/E	100	100	100	100	100	100
B/E	100	100	100	99.0	100	98.0
C/E	100	100	100	98.0	100	96.0
D/E	99.0	100	98.0	96.0	98.0	94.0
ABCD/E	99.60	100	98.0	96.40	98.50	88.0
A/D/E	99.33	98.0	100	96.67	100	99.0
AB/CD/E	99.20	100	99.33	97.20	98.0	98.67

Table 5
Results of the statistical test for the classification accuracy of methods.

Cases	A/E	B/E	C/E	D/E	ABCD/E	A/D/E	AB/CD/E
p-value	1	0.005	0.024	0.0325	0.005	0.007	0.005

related information can be learned by PCANet when the EEG matrices are generated in FFT domain. Besides the classification precision, this combined method has outperformed the single PCANet in terms of the robustness and stability. Notably, the greatest advantage of the FFT-based PCANet lies in the much lower volatility of results along with the switch. The results shown in Fig. 5 has also confirmed the superior capability of the proposed method for the identification of epileptic EEG. The AUC of our scheme is more evenly and extensively distributed in the radar chart.

The computing time is one of the crucial indicators that can intuitively reflect the complexity of algorithm. The more complex and time-consuming method tends to yield less on-line application value.

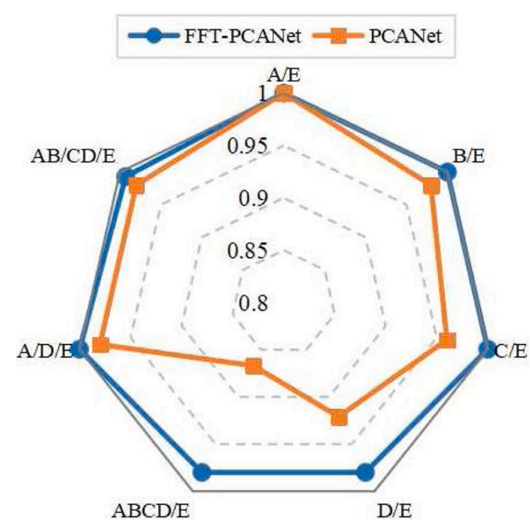

Fig. 5. The AUC for different classification tasks.

Therefore, we have investigated the execution time of some popular feature extractors. In order to entangle this issue, five commonly used non-linear features including approximate entropy (ApEn), FuzzyEn, sample entropy (SampEn), fractal dimension (FD) and Hurst exponent

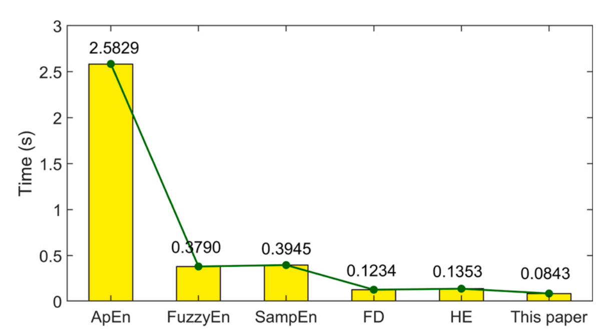

Fig. 6. The execution time required to extract the features from one EEG sample.

(HE) are calculated. Fig. 6 refers to the time required by different feature methods. Obviously, the proposed algorithm takes the shortest computing time of 0.0843 s under the same conditions. In total, the proposed scheme takes 0.0912 s to process an EEG signal segment and to yield a decision on which class it belongs. The PCANet method remarkably reduced the running time while maintaining a comparable performance relative to the traditional feature approaches. From the experimental results, we can see that this novel detection algorithm proves to be superior regarding execution time as compared to other features, which has gained a trade-off between the accuracy and computational cost with the presence of FFT-based feature learning strategy. The better efficiency has made it a highly favorable alternative for real-time EEG monitoring.

4.2. Classification performance on database B

In this section, we have further verified whether the model designed earlier woks on the long-term EEG database. According to the previous work [28,29], four distinct channels are selected based on quantitative measures of standard deviation (SD) and mutual information (MI). Moreover, the EEG data are divided into 4-s-duration segments by a sliding window without overlap. Then all the selected channels in each window are sequentially concatenated together to form a single EEG, which is subjected to this presented method to obtain the classification result. The recording length used for each patients has been listed in Section 2(See Table 2). The total duration of seizure is less than 2% of total duration of EEG records, which may lead to classifier bias toward detection of the majority class. Taking into account the extreme imbalance of the database, we have applied the adaptive synthetic sampling technique (ADASYN) [30] to create minority class samples.

Table 6 shows the patient-specific classification results provided by our proposed scheme (k_1=k_2 = 15, L_1=L_2 = 8, B = 25 × 25) as well as other studies. We can find that the average values for accuracy, sensitivity and specificity are 98.47%, 98.28% and 98.50%, respectively using our proposed method. The AUC obtained by proposed method is generally higher than 0.95 for different patients (See Fig. 7). The patient-specific results reported in this work are particularly outstanding in comparison to that described in [38,39], even for data groups chb06, chb12, chb14, chb15, chb16 and chb18 where epileptic segments are hard to discriminate. Deep features obtained by the FFT-based PCANet provides better representation, and therefore resulting in a sensitivity of not lower than 93% for each patient. It is worth mentioning that the proposed feature learning method has presented a relatively consistent performance for different patients in the EEG classification, thereby demonstrating the robustness of our method. Consequently, the proposed feature learning method concerned in this study is very effective to distinguish seizure events from both short- and long-term EEG signals, which hopes to be a reliable descriptor of a given signal.

Table 6
The patient-specific classification results.

Patient ID	Acc (%)	Sen (%)	Spe (%)
chb01	99.84	99.80	99.85
chb02	99.43	98.50	99.90
chb03	97.53	98.20	97.20
chb04	97.90	96.90	98.40
chb05	99.67	99.40	99.80
chb06	99.80	99.40	100
chb07	98.40	98.50	98.35
chb08	94.83	97.00	93.20
chb09	99.60	99.50	99.65
chb10	97.57	97.60	97.55
chb11	99.97	99.90	100
chb12	96.67	98.52	94.35
chb13	99.43	99.10	99.60
chb14	99.23	99.40	99.15
chb15	95.97	93.67	97.70
chb16	99.83	99.50	100
chb17	97.50	96.30	98.10
chb18	99.57	98.70	100
chb19	98.90	98.30	99.20
chb20	98.83	98.20	99.15
chb21	98.43	99.27	97.80
chb22	97.37	95.90	98.10
chb23	99.00	99.40	98.80
chb24	97.93	97.70	98.05
Average	98.47	98.28	98.50

4.3. Comparison with previous studies

Finally, the proposed method is also compared with some state-of-the-art epilepsy detection methods using the same databases. It could be noticed in Table 7 that the proposed method could produce significant classification accuracy for the same classification tasks compared to other studies. For the classification problem ABCD/E, the classification accuracy achieved from this study is 99.60% which is only 0.2% less than that presented in [37]. We would also like to mention that the EEG classification results yielded in this work are relatively close each other on all the concerned problems that are clinically significant, whereas some of the works fail to show stable results in case-wise performance. Additionally, the researchers of [32–37] focused more on the binary classification problems rather than multi-class problems. The existing techniques for the task of seizure detection in long-term EEG are tabulated in Table 8. The deep leaning model proposed in this study attains an average sensitivity of 98.28% by applying only 4 channels, which is comparable to other algorithms. The trade-off between Sen and Acc is encountered in [38,40], while the proposed method achieves a more balancing result with the presence of FFT-based feature learning strategy. This shows the effectiveness of the proposed algorithm in distinguishing seizure events, even with the variation of subjects or tasks. As expected, the deep features extracted from the frequency matrix of EEG signal using PCANet has provided better performance for the classification of EEG. All in all, the achieved results suggest that the feature learning method concerned in this study can acquire superior performance on both short- and long-term EEG.

4.4. Discussion

Epilepsy is a chronic brain disease with complex etiology. Due to the diversity of epileptic seizures, the hand-crafted features are only effective on some patients or some specific cases. No algorithm that could be considered satisfactory as a universal algorithm for seizure detection has emerged. This study proposes a FFT-based deep feature learning method for EEG classification that does not require manually create features with priori knowledge. The FFT is combined with the deep PCANet in a novel way and this hybrid method has achieved the promising results in seizure detection.

In this work, two authoritative databases are used to evaluate the designed model. The proposed method has adapted well to different EEG data, which can acquire superior performance on both short- and long-term EEG in comparison to the existing methods. From the perspective of a single database, our approach is also proved to be robust and stable since a relatively consistent performance is obtained across different patients or different classification tasks. The results from the current work affirm the potential use of our method in term of the robustness and stability. Furthermore, we has analyzed the cost effectiveness by computing the latency, where latency is the time delay it takes from the beginning of one EEG acquired to the end of a decision printed. It roughly consumes 0.0912 s to process an EEG epoch, which is significantly less than the length of an EEG segment. That is, the label has been produced before the next EEG comes.

The success of the proposed model can be attributed to the integration of FFT and PCANet. PCANet is a simple deep learning network that demonstrates a competitive performance with other deep networks. In

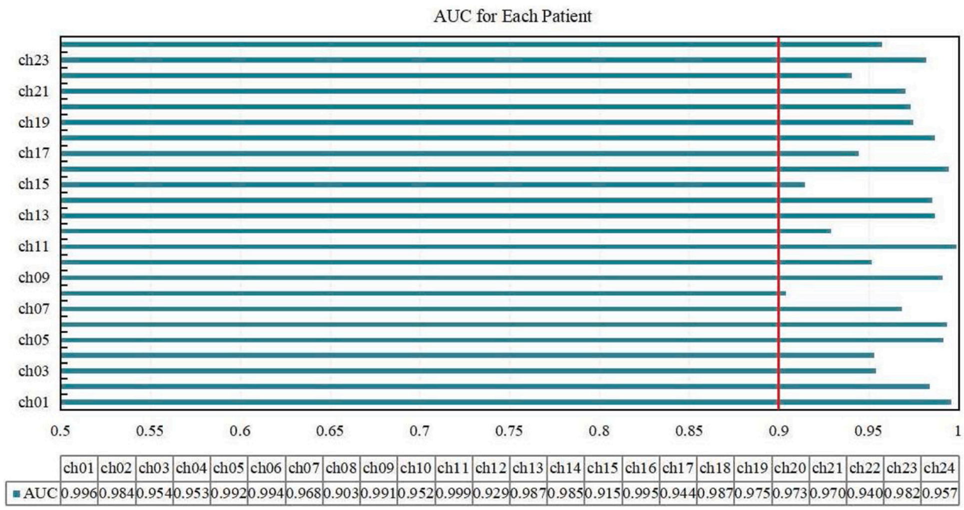

Fig. 7. The AUC of the proposed method for each patient.

Table 7
Comparison with other seizure detection methods using the Bonn EEG database.

Author	A/E	B/E	C/E	D/E	ABCD/E	A/D/E	AB/CD/E
Hassan et al. [31]	100	/	100	97	97.20	99	97.6
Samiee et al. [32]	99.8	99.3	98.5	94.9	98.1	/	/
Raghu et al. [33]	99.45	96.06	97.60	97.60	97.20	94.75	96.50
Jaiswal et al. [34]	100	99.5	99.50	95.50	97.40	97.20	97.43
Riaz et al. [35]	99.0	/	/	93.0	96.0	85	83
Sharma et al. [36]	100	100	99	98.5	99.20	/	/
Vidyaratne et al. [37]	/	/	/	/	99.80	/	/
This paper	100	100	100	99.0	99.60	99.33	99.20

Table 8
Comparison with other seizure detection methods using the CHB-MIT EEG database.

Author	Patients	Channels	Training Data (%)	Sen (%)	Spe (%)	Acc (%)
Zabihi et al. [38]	23	23	50%	94.80	94.69	89.10
Kaleem et al. [39]	23	23	5 fold CV	94.27	91.55	92.91
Fergus et al. [40]	24	23	80%	88.0	88.0	93.0
Selvakumari et al. [41]	24	12	50%	95.70	96.55	95.63
Vidyaratne et al. [37]	22	23	Leave one out CV	96.2	/	/
Tian et al. [42]	24	23	25%	96.70	99.10	98.30
Bhattacharyya et al. [29]	24	5	10 fold CV	97.91	99.57	99.41
Tang et al. [43]	20	5	Leave one out CV	97.2	/	97.8
This paper	24	4	10 fold CV	98.28	98.50	98.47

addition, we have studied the effects of all the PCANet parameters to find an optimal solution for EEG analysis. The FFT has been explored in a novel way to generate the EEG matrix, which provides the better frequency representation for EEG. A PCANet with optimized structure is designed to learn the distinctive information of EEG signals. Interestingly, the proposed scheme reaches high accuracy without increasing the computational burden. Therefore, our both these operators work in tandem to learn the valuable EEG features, in a fast and automatic manner.

As compared to the existing FFT-based seizure detection methods, the advantages of the proposed method are: 1) The proposed algorithm is of great generalization, making it a promising candidate for expanding into other patient groups. 2) The algorithm provide better results without aggravating computational complexity. 3) It has overcome the shortcoming of hand-crafted features. Despite the superiority, the limitation of this research is that the proposed model is validated only in laboratory stage, it is interesting to see the behavior of our method in the clinical trials and experiments using large amounts of actual EEG from various patients. And the model can be further simplified by optimizing the process of key-points.

5. Conclusion

The EEG-based intelligent diagnosis technology will become mainstream in the 21 st century. In this article, a unique approach has been developed to capture the subtle information hidden in EEG, which overcomes the shortcoming of hand-crafted features. The deep learning model has been explored in a novel way to learn EEG features. The main contributions of this paper lies on the construction of a PCANet for epileptic EEG classification and the use of FFT to generate the inputs to the PCANet. The involved parameters are carefully fine-tuned in order to obtain a deep learning model with optimal classification accuracy and generalization capability. The proposed scheme is tested by two challenging databases that are available online. The experimental results have demonstrated the superior performance for both short- and long-term EEG analysis. The FFT-based deep features can enhance the detection performance when compared with the conventional feature extraction methods. The proposed technique is proven to be a robust and accurate model that has great flexibility and extensibility for the practical implementation. In the future work, the method will be refined to simplify the program into clinical development. Furthermore, we plan to study the potential of using proposed architecture for the diagnosis of other brain disorders such as schizophrenia disease, depressive disorder and more.

CRediT authorship contribution statement

Mingyang Li: Conceptualization, Methodology, Formal analysis, Software, Writing - original draft. **Wanzhong Chen:** Conceptualization, Validation, Supervision.

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Declaration of Competing Interest

The authors report no declarations of interest.

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