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Classification Epileptic Seizures in EEG Using Time-Frequency Image and Block Texture Features

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ABSTRACT With the rapid development in technology, computer aided detection or diagnosis has become an indispensable part of the medical industry. Automatic detection of epileptic events is one of the important subjects that have aroused wide interest from more and more investigators. This paper proposes a new model in classification of multi-category electroencephalogram (EEG) signals using time-frequency image and block texture features. The one-dimensional EEG is first mapped to time-frequency domain by means of short-time Fourier transform (STFT), which is adapted to obtain a two-dimensional time-frequency image (2D-TFI). With the idea of multi-scale blocking, the obtained phase images and amplitude images are divided into several sub-blocks corresponding to different frequency ranges and time periods. Then the texture features are calculated to describe the behaviour of EEG signals. Particularly, a novel quadratic feature selection method based on kernel entropy component analysis (KECA) and Kruskal-Wallis test (KW) has been proposed for dimension reduction, by which the features that contained most distinctive information were provided. Eventually, the optimal KECA-based features are fed to support vector machine (SVM) for deciding the class of corresponding EEG. The proposed model is found to achieve at least 99.30% accuracy, 98.0% sensitivity and 100% specificity for each of the eight clinical problems. Our scheme is proven to be effective for seizure detection, which can help doctors optimize the diagnosis workflow, reduce workload and improve detection precision.

INDEX TERMS Seizure, EEG, two-dimensional time-frequency image, multi-scale blocking, texture features, kernel entropy component analysis, quadratic feature selection.

I. INTRODUCTION

Epilepsy is a chronic disorder of the brain that can affect individuals of all ages, often accompanied by convulsions, loss of consciousness and other symptoms [1], [2]. According to WHO statistic, globally 50 million people are suffering from epilepsy, of which 80% live in developing countries [3], [4]. People with epilepsy would be destined to not only bear physical pain but also burdened with more misunderstanding and social stigma. Electroencephalogram (EEG) is a useful tool for emotion classification [5] and diagnosis of brain diseases [6], which provides convenient, non-intrusive and more accurate way of capturing brain signals. Electroencephalogram (EEG) and symptom are the only two necessary criteria for epilepsy diagnosis in clinic. As an effective technology of medical imaging, EEG can directly measure the neural electrical activity of brain with a high temporal resolution [7]. The traditional method of manual monitoring is to visually inspect 24-hour EEG recordings by neurologists, which is proved to be a time-consuming, error-prone and tedious process [8], [9]. Therefore, there is a dire need of reliable techniques for detecting seizures automatically and accurately. Such a computer aided diagnostic system can help to relieve the workload of doctors and provide more effective and affordable medical service for patients.

A successful detecting model should realize accurate analysis and interpretation of EEG. It requires scholars to

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be committed to the major aspects involved in a detection method: (i)feature extraction, (ii) the feature classification [10]. EEG feature extraction and description is one of important research topics in pattern recognition, which significantly contribute to the performance of the classifier and reduce data size without losing its distinguishing power. Thus, this present study is concentrated particularly on searching for an effective feature extraction method rather than designing the structure of a complex classifier. Till date, numerous methods have been carried out in the literature to extract features of interest. The following are some of the seminal studies. Mohammadpoory *et al.* [11] proposed a new method based on weighted visibility graph entropy (WVGE) to identify normal, ictal and interictal groups EEG signals. The performance of features extracted from WVGEs are investigated by four popular classifiers. Das and Bhuiyan [12] reported an approach to distinguish focal and non-focal EEG signals using entropy-based features in the combination of empirical mode decomposition (EMD) and discrete wavelet transform (DWT) domain. The authors calculated the Shannon entropy, log-energy entropy and Renyi entropy in the EMD-DWT domains to characterize EEG signals. Song *et al.* [13] came up with a seizure detection model on the basis of the Mahalanobis distance and DWT. They confirmed the idea of utilizing a fusion feature combining the Mahalanobis-similarity-based feature with sample entropy (SampEn) for complexity description. Junhui *et al.* [14] presented a novel method for seizure detection using sparse representation with elastic net constraint over a learned dictionary. The procedures of extracting features and selecting classifiers were not required in their framework, which was different from traditional seizure detection methods. Lee *et al.* [15] adopted wavelet transform, phase-space reconstruction, and Euclidean distance to identify normal and epilepsy EEG, where a neural network with weighted fuzzy membership functions was presented to improve the performance. Bhattacharyya and Pachori [16] identified seizure onset patterns by employing empirical wavelet transform (EWT). The authors have reported promising results in the detection of seizure events appearing in long EEG recordings. As pointed in [17], a method based on tunable-Q wavelet transform (TQWT) was proposed to classify the focal and non-focal types of EEG signals. In his study, multivariate fuzzy entropy was obtained from the sub-band EEG signals.

From the state of art, it is observed that most of the existing works are not sufficient enough to provide good classification accuracy when dealing with all the cases that are clinically significant. The reported methods are limited in their ability of robustness and generalization, although they have achieved different levels of success for a certain case. Seldom of the prior methods considered a two-dimensional time-frequency image (2D-TFI) for describing EEG, where extraordinary characteristics will be revealed from different perspectives. In allusion to the problems mentioned above, this research intends to design a novel framework for feature extraction from the perspective of multi-scale 2D-TFI segmentation. In this paper, the feature extraction problem explores not just how to obtain the discerning features, but how to remove the redundant ones from the original feature set. In this regard, we introduce the thought of quadratic feature selection in order to obtain better representative features in non-stationary EEG signals. To the best of our knowledge, the algorithmic structure of quadratic feature selection have not been used on the epileptic EEG data so far. In particular, our proposed method is proceeding on the basis of short-time Fourier transform (STFT) and kernel entropy component analysis (KECA). It is also worth mentioning that local binary patterns (LBP) is verified to be an excellent tool in image processing due to its discriminating power and computational simplicity. Therefore, the LBP is exploited for texture analysis of 2D images in this study. The objective of the study is to explore a feasible approach with better classification accuracy and generalization ability, which could be extended to the real-time implementation for seizure monitoring.

The remaining paper is structured in the following manner. Section II provides a general introduction of the proposed framework. Section III briefly describes the EEG database. Section IV, Section V and Section VI introduce the basic theory of the methodology adopted in this study. The experimental results and discussions of the entire work are given in Section VII while Section VIII is devoted to the conclusions.

II. ARCHITECTURE OF THE PROPOSED ALGORITHM

This work present a hybrid model for seizure detection using time-frequency image based block texture features. The idea of image analysis is introduced for epilepsy diagnosis in this dissertation, which provides a new path to process EEG signal. Along with this, eight classification problems are considered to assess the performance of our method. The complete algorithm encompasses three principal stages: (1) EEG signal is firstly converted to time-frequency domain by performing STFT. Under such a premise, we can plot two 2D-TFI with the acquired matrices of amplitude coefficients and phase coefficients for texture analysis. (2) Once LBP features based on sub-block images are extracted, the KECA in alliance with Kruskal-Wallis test (KW) is employed on the second stage to lessen the dimension and remove the redundancy. (3) Eventually, the optimal features are fed to support vector machine (SVM) for deciding the class of the corresponding EEG. The overall architecture of our proposed method is depicted in Fig. 1.

III. MATERIALS

The public database used in this paper is obtained from the Department of Epileptology, Bonn University [18]. The database consists of five sets (denoted A-E) with each including 100 single-channel EEG segments of 23.6 duration, sampled at rate 173.61 Hz and 12 bit A/D resolution. For convenience, a concise summary of the database is tabulated in Table 1. Sets A and B were surface EEG recordings taken from five healthy volunteers with eyes open and closed,

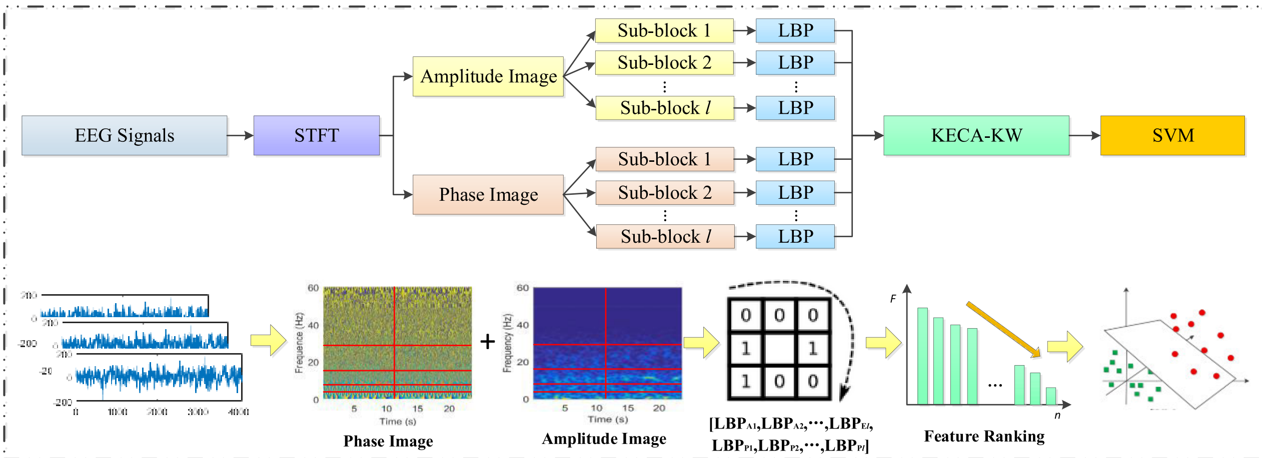

FIGURE 1. Overall architecture of the proposed method. EEG signal is converted to time-frequency domain by STFT. And amplitude image and phase image are plotted and divided into *l* sub-blocks which are subject to LBP analysis. Then KECA-KW is introduced to lessen the dimension and remove the redundancy and the selected features are fed to SVM classifier.

TABLE 1. Concise information of the database.

Sets	Subjects	Subjects' state	Electrode placement	Electrode type
Set A	Five healthy volunteers	Awake and eyes open	International 10-20 system	Surface
Set B	Five healthy volunteers	Awake and eyes closed	International 10-20 system	Surface
Set C	Five epileptic patients	Seizure free	Opposite to epileptogenic zone	Intracranial
Set D	Five epileptic patients	Seizure free	Within epileptogenic zone	Intracranial
Set E	Five epileptic patients	Seizure	Within epileptogenic zone	Intracranial

respectively. The remaining three sets (Sets C-D) were all collected from five epileptic patients. It should be stressed that the EEG data in Sets C and D correspond to seizure-free activity, whereas the recordings in Set E correspond to seizure activity. Fig. 2 shows the sample EEG signals from five sets. The stability plays an important role in algorithm evaluations with regard to the clinical needs. In order to ascertain whether the method works on various conditions, all the five sets have been applied to constitute eight cases of classification in the present research. These tasks are described as:

1. Set A vs Set E: Normal vs Seizure
2. Set B vs Set E: Normal vs Seizure

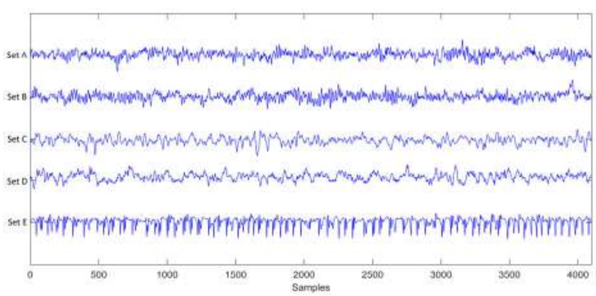

FIGURE 2. Sample EEG signals from each of the five sets. Sets A and B are surface EEG recordings taken from five healthy volunteers with eyes open and closed, respectively. The EEG data in Sets C and D correspond to seizure-free activity, whereas the recordings in Set E correspond to seizure activity.

3. Set C vs Set E: Seizure-free vs Seizure
4. Set D vs Set E: Seizure-free vs Seizure
5. Sets A-D vs Set E: Non-seizure vs Seizure
6. Sets A B vs Sets C-E: Normal vs Abnormal
7. Sets A vs Set D vs Set E: Normal vs Seizure-free vs Seizure
8. Sets A B vs Sets C D vs Set E: Normal vs Seizure-free vs Seizure

IV. TFI BASED SUB-BLOCK FEATURE EXTRACTION

This study proposes a new feature extraction approach based on time-frequency representation (TFR) and image processing, which is different from the approaches presented in previous studies. The relevant steps are explained in this part.

A. TIME-FREQUENCY REPRESENTATION

Time-frequency representations (TFR) has been important for analysis of non-stationary EEG signals, where transient features can be captured and localized precisely from both time domain and frequency domain. The classical time-frequency analysis, such as STFT, has proven to be a powerful tool for analyzing epileptic EEG and has also been widely used for seizure detection due to its flexibility and practicality [19], [20]. STFT is applied by shifting the window function on the short segments and enforcing the Fourier transform (FT) analysis on each of these segments [21]. In this paper, STFT is investigated to produce a 2D image representation of EEG signals and the mathematical formula is defined as [22], [23]:

$$F_{stft}(u,f) = \int_{-\infty}^{\infty} x(t)g(t-u)e^{-j2\pi ft}\,dt \tag{1}$$

where $x(t)$ is the signal to be transformed and $g(t)$ is the sliding window function. The STFT coefficients are consist of real part and image part. Through STFT, the amplitude spectrum $A(u,f)$ and phase spectrum $\Phi(u,f)$ are given as:

$$A(u,f) = \sqrt{\{\mathrm{Re}[F_{stft}(u,f)]\}^2 + \{\mathrm{Im}[F_{stft}(u,f)]\}^2} \tag{2}$$

$$\Phi(u,f) = \arctan\{\frac{\mathrm{Im}[F_{stft}(u,f)]}{\mathrm{Re}[F_{stft}(u,f)]}\} \tag{3}$$

where $\mathrm{Re}(\cdot)$ and $\mathrm{Im}(\cdot)$ are two functions to acquire the real part and the imaginary part of a complex signal, separately. The Hamming window with 1024 length is used.

The amplitude distribution and phase distribution of EEG signal are displayed in the form of 2D-TFI, so the method of image processing can be used to handle the problem of seizure classification.

B. TFI BLOCK

Image blocking is a crucial step of this algorithm model that transits from image process to image analysis. The sub-image contains plenty of physiological and pathological information for detecting seizure from EEG. The amplitude image and phase image are related to both time and frequency. In this concept, a image segmentation method based on multi-scale blocking idea (including time scale and frequency scale), which boasts simplicity and high recognition rate, is proposed. That is to say, the obtained TFI can be divided into some sub-blocks corresponding to different frequency ranges and time periods to localize significant structures. Since EEG basic rhythms in different brain states possess different features, we intend to divide TFI into five modules corresponding to the EEG rhythms. The main rhythms carrying out clinical and physiological interest fall primarily in five frequency ranges: Delta (0-4Hz), Theta (4-8Hz), Alpha (8-15Hz), Beta (15-30Hz), Gamma (30-60Hz). Additionally, each rhythm-based sub-block is further segmented into some parts of equal intervals along the timeline. The sliding window length of time domain is set to 11.8s (more on this below). An illustration of the segmentation principle is shown in Fig. 3.

C. TEXTURE ANALYSIS

Texture features has been suggested for classification of epileptic seizure EEG signals [24]–[26]. Motivated by the low computational complexity, we utilize LBP on the divided 2D-TFI for texture analysis. LBP, introduced by Sun *et al.* [27], is considered as one of the most effective local descriptors that can provide both local statistical information and spatial information [28]. At a given local region (p, r), the binary LBP code is produced by comparing the central pixel g_c with its neighbors g_p. This process can be defined as:

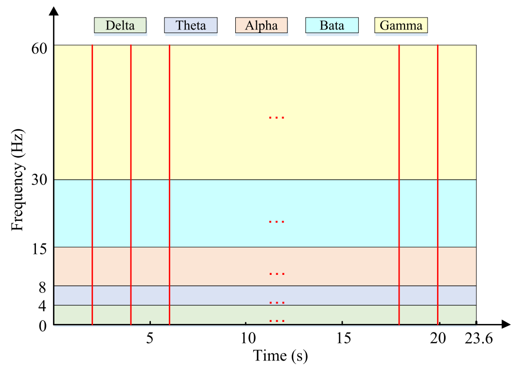

FIGURE 3. A diagram of the segmentation principle. The frequency window is changed according to five EEG rhythms and the time window maintains the fixed length.

$$LBP_{(p,r)} = \sum_{p=0}^{p-1} s(g_p - g_c)2^p \tag{4}$$

$$s(g_p - g_c) = \begin{cases} 1, & g_p - g_c \geq 0 \\ 0, & g_p - g_c \leq 0 \end{cases} \tag{5}$$

where r indicates the radius from center pixel, p is the total numbers of involved neighborhood pixels. After the above procedure, the generated binary codes are translated into decimal expressions, then a distribution histogram is built for texture characterization. The formula is written as below:

$$H(k) = \sum_{i=1}^{N}\sum_{j=1}^{M} f(LBP_{(p,r)}(i,j),k) \tag{6}$$

$$f(x,y) = \begin{cases} 1, & x = y \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

where H refers to the histogram of a $N \times M$ image and k indicates one LBP pattern. Fig. 4 shows the encoding process of the basic LBP operator ($p = 8$, $r = 1$). The possible patterns (2^p) increase sharply with the increase of sampling pixels on the circle. Since overmuch patterns are not conducive to texture expression, the uniform pattern (denoted as LBP^{u2}) is used to tackle this problem. The uniform pattern is an important extension of LBP, which contains at most two bitwise transitions from 0 to 1 or 1 to 0 when the binary string is considered as a circular [29]. By this way, the number of binary patterns is greatly reduced to 58 without loss of information. The sample of LBP features for one TFI block is illustrated in Fig. 5.

V. KECA-BASED QUADRATIC FEATURE SELECTION

The main challenge of feature selection is how to pick out some features that convey more useful classification-related information. We thus present a novel and effective feature selection strategy by integrating KECA and KW into one unit.

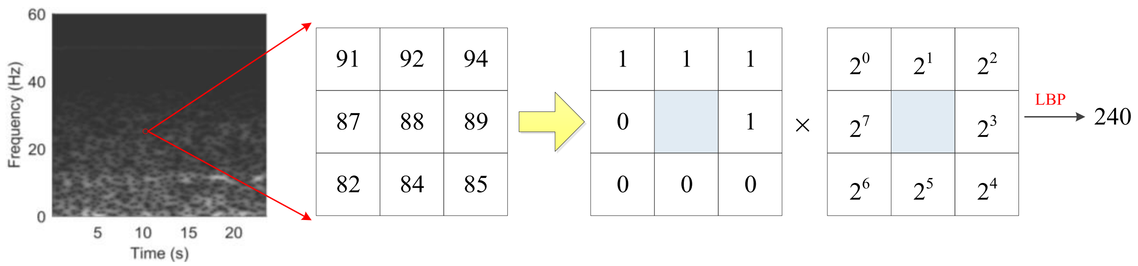

FIGURE 4. An example of the LBP operator. A pixel region is encoded as 240 through LBP.

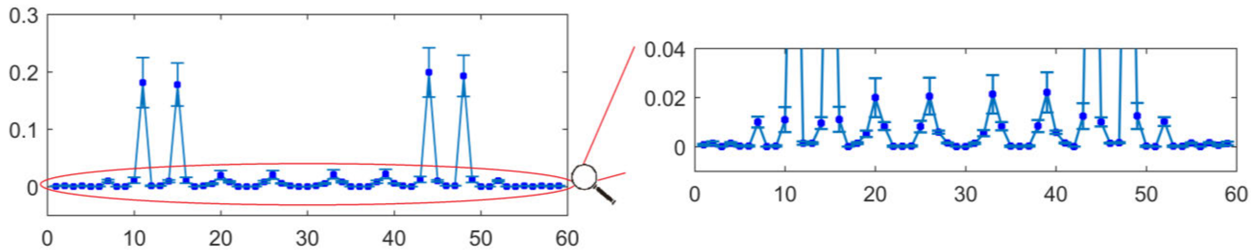

FIGURE 5. Sample of the LBP features for one EEG TFI block.

A. KECA

KECA is a newly developed information-theory-based method for data transformation and dimensionality reduction, which introduces the concept of Renyi entropy based on kernel principal component analysis (KPCA) [30]. The main advantage of KECA is that the principal components (PC) are selected according to the degree of contribution to Renyi entropy instead of the top n eigenvalues of the kernel matrix. This property makes KECA become a better alternative in comparing to KPCA and principal component analysis (PCA).

For sample X with N dimensions, the Renyi entropy is expressed as [31]:

$$H(p) = -\lg \int p^2(x)dx \tag{8}$$

where $p(x)$ is the probability density function. Since the logarithmic function is a monotonic function, we can focus on the quantity:

$$V(p) = \int p^2(x)dx \tag{9}$$

Then the Eq. (9) is estimated with the help of Parzen window density estimator which is given by:

$$\hat{p}(x) = \frac{1}{N}\sum_{x \in X} k_\sigma(x, x_t) \tag{10}$$

where $k_\sigma(x, x_t)$ is the so-called Parzen window function, σ is the width of kernel function. Using the sample mean approximation of the expectation operator, we have:

$$\begin{aligned}\hat{V}(p) &= \frac{1}{N}\sum_{x_t \in X}\hat{p}(x_t) = \frac{1}{N}\sum_{x_i \in X}\frac{1}{N}\sum_{x_j \in X}k_\sigma(x_i, x_j)\\ &= \frac{1}{N^2}L^T K_\sigma L \end{aligned}\tag{11}$$

where L represents an unit vector with length N, K_σ is a $N \times N$ kernel matrix which can be decomposed as $K_\sigma = \mathrm{EDE}^T$. In this equation, D is the diagonal matrix constituted by eigenvalues $\lambda_1, \lambda_2, \ldots, \lambda_N$ and each column in $E = [e_1, e_2, \ldots, e_N]$ is the eigenvector corresponding to one of the eigenvalues. And Eq. (11) is rewritten as:

$$\hat{V}(p) = \frac{1}{N^2}\sum_{i=1}^{N}(\sqrt{\lambda_i}e_i^T L)^2 \tag{12}$$

KECA is defined as an m-dimensional data transformation obtained by projecting ϕ_{eca} onto a subspace spanned by principal axes U_m corresponding to the top entropy values, the expression of extracted KECA features is:

$$\phi_{eca} = D_m^{1/2}E_m^T \tag{13}$$

Obviously, it is noted that the sum of elements in eigenvectors also has great effects on the estimation of Renyi entropy besides the eigenvalues of kernel matrix. So KECA presents better cluster structure and more label information.

B. KRUSKAL-WALLIS TEST

The PCs derived from KECA are ranked in decreasing order of the entropy. Generally, the first k PCs are simply selected as new feature vectors to characterize EEG signals. However, the PCs with a small contribution rate that is discarded may posses certain unique patterns, so it can not meet the anticipated performance of using KECA in the traditional manner. To address this issue, we have integrated Kruskal-Wallis test (KW) into KECA. KW is a non-parametric form of the Analysis of Variance (ANOVA) and can be used to assess whether the difference between two or more independent data groups is statistically significant [32]. The popularity of KW may be attributed to its non-necessity of the assumptions about normal distribution.

In this paper, difference among the PCs is deemed as a criteria when performing a secondary selection based on KW. Those features with significant difference tend to be of higher validity in subsequent steps. In this concept, KECA is firstly used to obtain n PCs that contribute most to the Renyi entropy, and then a secondary selection is conducted on PCs using KW. KW test is carried out with consideration the F-value. The higher is the F-value, the better discrimination is the feature [33]. We calculate a F-value for each component in EEG feature vector, and all the features are sorted in the decreasing order of their F-values. The features are added one by one in accordance with the order and are subject to SVM for classification. Through experiment, it makes sure that $n = 50$ is satisfied in this paper. A flow chart of KECA-KW method is displayed in Fig. 6.

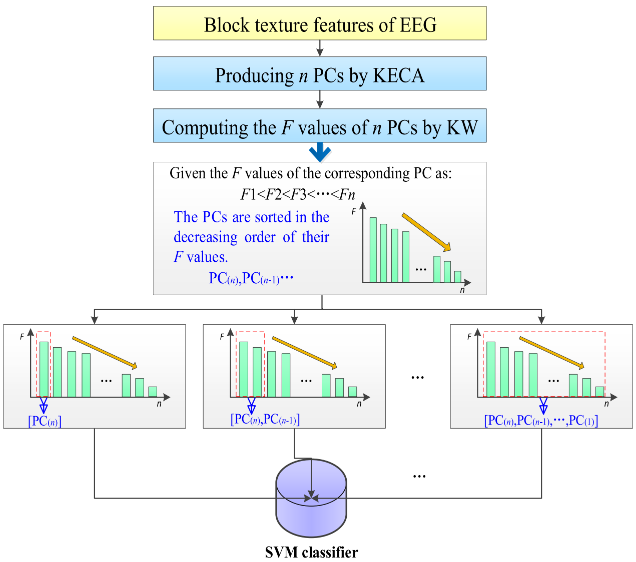

FIGURE 6. **A flow chart of KECA-KW method. KECA is firstly used to obtain *n* PCs that contribute most to the Renyi entropy, and then a secondary selection is conducted on PCs using KW. Next, the feature ranking method is used.**

VI. SUPPORT VECTOR MACHINE

The SVM is known as a classical machine learning technique which has shown state of the art performance in EEG recognition. The basic principles of SVM can be found in literature [34], [35]. In this study, we adopt SVM configured with a kernel of radial basis function (RBF) in classification of epileptic seizure. More specifically, the involved parameters, namely regularization parameter and kernel parameter, are automatically optimized by grid search. Additionally, other types of classifiers are also assessed for EEG discrimination, which includes linear discriminant analysis (LDA), decision tree (DT), and K-nearest neighbor (KNN). As expected, SVM stands out with perfect classification capability and spreading potential, becoming the selected classifier in our model. The parameter setting for classifiers is listed below:

SVM: Cost $C = 2$, Sigma $\sigma = 1$.

KNN: Nearest neighbor $K = 2$.

DT: Max split nodes $MaxNS = 6$.

VII. RESULTS AND DISCUSSION

All the experiments of this section are implemented in Matlab 2016b and run on a 3.70 GHz Core i3 processor machine with 4 G RAM.

A. PERFORMANCE EVALUATION

In this section, we have presented the experimental results that are measured in terms of three well-known indexes including sensitivity (Sen), specificity (Spe) and accuracy (Acc) [36]. The formulas of these three metrics are defined as follows:

$$\mathrm{Acc} = (\mathrm{TN} + \mathrm{TP})/(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}) \tag{14}$$

$$\mathrm{Sen} = \mathrm{TP}/(\mathrm{TP} + \mathrm{FN}) \tag{15}$$

$$\mathrm{Spe} = \mathrm{TN}/(\mathrm{TN} + \mathrm{FP}) \tag{16}$$

where TP is the number of true positive records, TN is the number of true negative records. Similarly, FP and FN denote the number of false positive and false negative records, respectively.

B. RESULTS

To investigate the robustness of our proposed model, we have carried out a series of experiments on eight clinical relevance tasks. In this research, EEG at a frequency above 60 Hz is first eliminated by a Butterworth low pass filter. Then STFT is used to transform the EEG into a series of coefficients, the amplitude and phase distributions of EEG in the TFR that can demonstrate the target characteristics are generated in form of 2D-TFI. Fig. 7 shows the amplitude images and phase images of five sample EEG. The qualitative discrimination of five types EEG is emerged visually from Fig. 7. The obtained images are divided into $5 \times k$ non-overlapping blocks for texture analysis and each of the sub-images is described by a uniform pattern LBP. Then the histograms of LBP codes are concatenated into the original feature vectors which are stored for further selection using KECA-KW. Having obtained the suitable and discriminating features, SVM is constructed to determine which class the EEG belongs.

The number of image blocks is one of the important factors affecting the quality of our model. As mentioned before, the image is divided into $5 \times k$ non-overlapping regions along the frequency-axis and time-axis. Each region points out a specific EEG rhythm in a certain time period. Based on the basic LBP^{u2} ($p = 8$, $r = 1$) operator, it will result in a total $58 \times 5 \times k$ feature elements when we divide the time axis into k equal windows. The choice of a appropriate k can improve the capability of EEG representation while maintaining the algorithm complexity. In this regard, the parameter k is set to 1, 2, 3, 4, relatively. The average accuracy acquired after 10-fold cross-validation on eight classification tasks with different k values are summarized in Table 2. For the classification tasks concerned in the study, we have achieved better classification results with less features by considering $k = 2$. Nevertheless, it does not mean that the number of blocks is the more the better, because the increase of feature can gradually aggravate

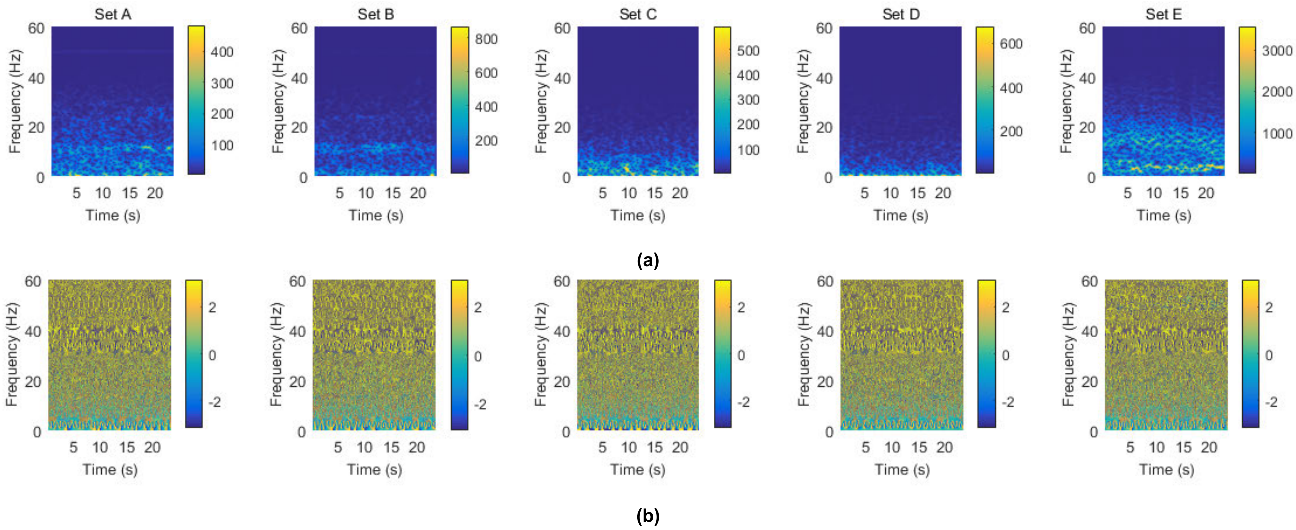

FIGURE 7. The 2D-TFI of five sample EEG: (a) Amplitude Image, (b) Phase Image.

TABLE 2. The best accuracy of eight classification tasks using different k values. Better classification results are yielded with less features by considering $k = 2$.

Cases	k=1		k=2		k=3		k=4	
	Acc	No. of PCs	*Acc*	No. of PCs	*Acc*	No.of PCs	*Acc*	No. of PCs
Case 1	99.50±1.58	24	100	10	98.50±2.41	18	100	17
Case 2	100	17	100	15	99.50±1.58	31	100	21
Case 3	99.50±1.58	15	100	24	99.0±2.11	24	99.50±1.58	15
Case 4	99.0±2.10	28	100	27	99.0±3.16	27	98.50±2.42	28
Case 5	99.20±1.39	40	99.60±0.84	23	98.60±1.35	33	98.40±1.26	41
Case 6	99.0±1.41	41	99.80±0.63	28	99.0±1.70	30	99.20±1.39	47
Case 7	99.0±1.61	35	99.33±1.41	30	98.0±2.33	37	98.67±1.72	35
Case 8	98.80±1.40	48	99.60±1.26	27	98.20±1.99	24	98.80±1.40	38

the information redundancy. And the computing time for the process of feature extraction and selection ($k = 2$) comes to 2.527s in total, which can completely meet the demands on practical use. Particularly, the detail performance under the premise of $k = 2$ is shown in Table 3. From Table 3, the accuracy for Cases 1-8 is found to be 100%, 100%, 100%, 100%, 99.60%, 99.80%, 99.33% and 99.60%, respectively. It is worth emphasizing that the *spe* has reached up to 100% for all cases, which indicates a better discrimination capability of the TFI based blocking texture features. Furthermore, there is very little up-and-down-motion among the *Acc* when our approach switches from one task to another. All that suggests that our proposed model is of great robustness in analysis of epileptic EEG signals on both two-class and three-class classification problems.

The change of the performance caused by using single amplitude or phase image based features is also discussed. The results are displayed in Table 4. Generally high classification accuracy is obtained from the methodology based on the combination of amplitude and phase images, because features from the two TFI work in synergy to create greater representation than either of them alone. It is found that the proposed method has distinct advantages over other methods on the respects of robustness, adaptability and multitasking.

TABLE 3. The specific performance delivered by setting $k = 2$.

Cases	*Acc*	*Sen*	*Spe*	No. Of PCs
Case 1	100	100	100	10
Case 2	100	100	100	15
Case 3	100	100	100	24
Case 4	100	100	100	27
Case 5	99.60±0.84	98.0±4.21	100	23
Case 6	99.80±0.63	99.67±1.05	100	28
Case 7	99.33±1.41	99.0±2.11	100	30
Case 8	99.60±1.26	99.33±1.24	100	27

Fig. 8 depicts the preliminary screening features generated by KECA in the case of $k = 2$. The discrimination ability of preliminary screening features is quantified using KW. Fig. 9 provides the F-value of the selected PC, and certain

TABLE 4. The performance using different TFI based features. Generally high classification accuracy is obtained from the methodology based on the combination of amplitude and phase images.

Cases	Phase Images		Amplitude Images		Phase Images+ Amplitude Images	
	Acc	No. Of PCs	*Acc*	No. Of PCs	*Acc*	No. Of PCs
Case 1	98.50±2.42	37	97.50±2.64	20	100	10
Case 2	99.50±1.58	14	96.50±4.12	6	100	15
Case 3	100	42	99.50±1.58	24	100	24
Case 4	99.0±2.11	46	98.50±3.53	3	100	27
Case 5	98.80±1.03	39	98.40±1.35	49	99.60±0.84	23
Case 6	97.80±2.57	18	95.80±2.39	27	99.80±0.63	28
Case 7	97.33±3.78	31	96.67±2.72	46	99.33±1.41	30
Case 8	96.80±2.53	45	97.40±1.88	35	99.60±1.26	27

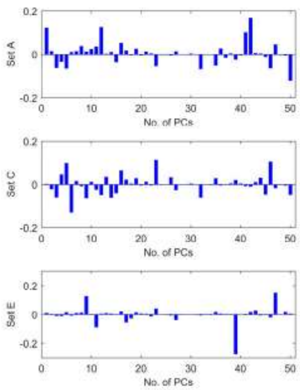

FIGURE 8. The preliminary screening features for five sets.

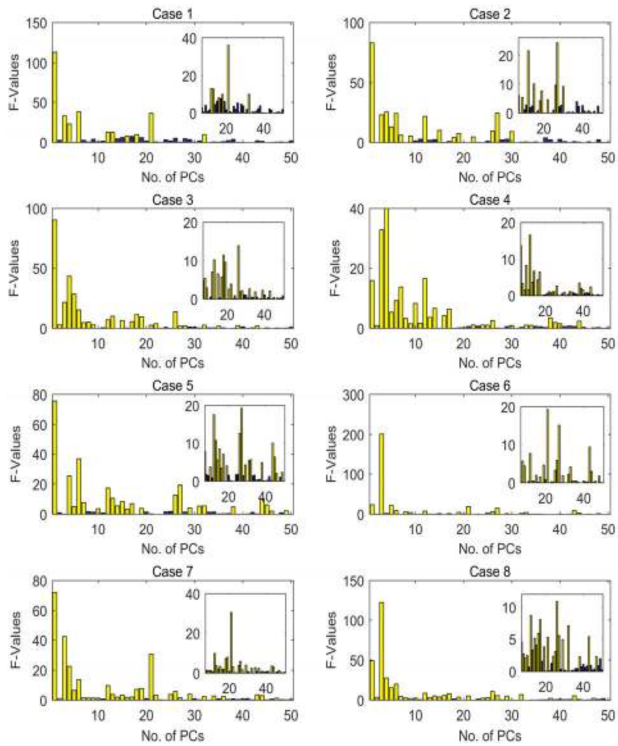

FIGURE 9. The preliminary screening features for five sets. Certain position (7-50) is partially enlarged and the bars marked in yellow represents the optimal feature combinations used to achieve the best classification results tabulated in Table 3.

position (7-50) is partially enlarged. The bars marked in yellow represents the optimal feature combinations used to achieve the best classification results tabulated in Table 3. It can be noted that the PC with small contribution rate often contains more specific information which is necessary for improving classification precision. This indicates that specificity of PC is not closely tied with its contribution rate. However, KW provides a possible way to measure the relative importance of the selected PCs. Most pointedly, KW just makes up the shortcoming of the KECA and avoid the omission of PC which is of small contribution rate but of high discrimination. In summary, the combination of KECA and KW has strengthen the representation ability of features and also reduced the computational cost.

In order to highlight the superiority of the proposed KECA-KW method, a comparative experiment of different feature selection techniques is designed in this part. In order to entangle this issue, experiment steps and parameters remain the same except the feature selection methods. The performance of various feature selection methods is provided in Fig. 10. It is evident from the figure that the proposed KECA-KW method outperforms the other two independent methods, which has yielded a superior accuracy using the least features. In particular, these results of the three methods are significant different when dealing with Cases 5-6. Obviously, this compound algorithm has a higher detection performance than use each of them alone. The significant increase in the accuracy rates mainly attributed by the combination of KECA and KW. This demonstrates the usefulness of the compound technique, both in terms of efficiency and effectiveness.

KW just makes up the shortcoming of the KECA and avoid the omission of PC which is of small contribution rate but of high discrimination. KECA can remove the redundant information caused by the multi-scale blocking LBP features. Hence, the fusion of KECA and KW can make remedies to the disadvantages of both methods and play an crucial role in

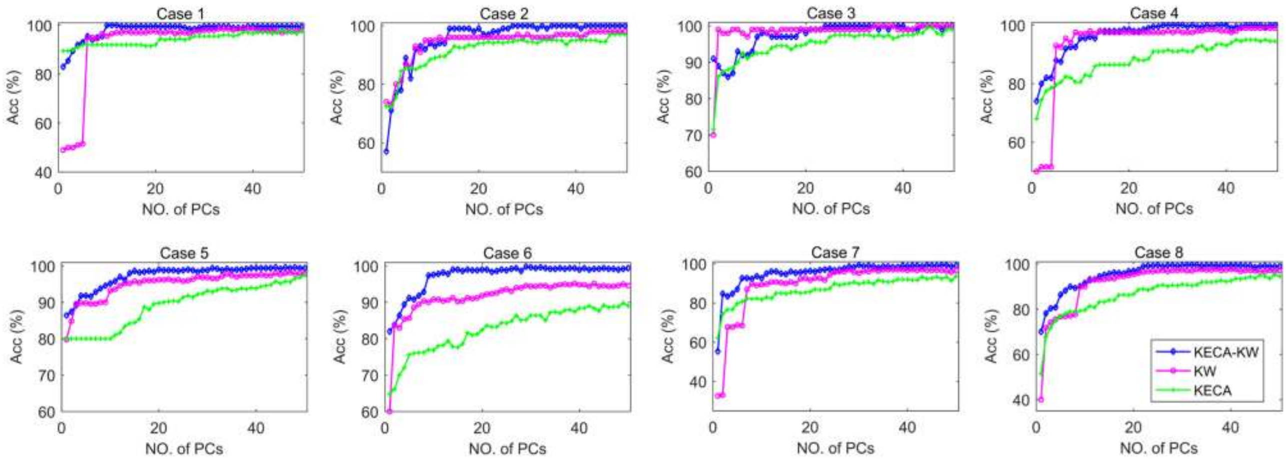

FIGURE 10. The performance of various feature selection method. The proposed KECA-KW method outperforms the other two independent methods, which has yielded the superior accuracy with the least features.

improving the overall performance of the proposed model. This method enables specification analysis and eliminate redundancy in the cluster.

With the appropriate extracted features, another main problem is to select an efficient classifier to complete the seizure detection. Specific estimates for several common classifiers have been taken into account in this scheme. In this part, we compare the classification ability of LDA, KNN, DT and SVM for seizure recognition using the same TFI-based features. As observed from Fig. 11, SVM has achieved better and stabler classification performance of epileptic seizure detection than the other three classifiers under the small study sample condition, especially for Cases 6-8. Furthermore, the gap in the results achieved by a same classifier is pronounced between different cases, except for SVM. By contrast, SVM is probably a more appropriate choice for our detection model.

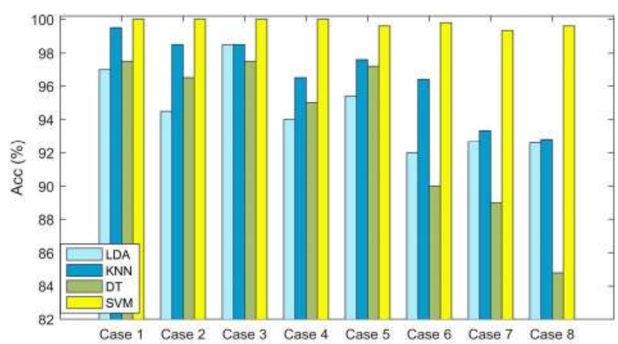

FIGURE 11. Performance comparison among four different classifiers. SVM has achieved better and stabler classification performance of epileptic seizure detection than the other three classifiers under the small study sample condition, especially for Cases 6-8.

C. COMPARISON WITH EXISTING WORKS

In order to evaluate the potentials of presented scheme, we present a summary of the results reported in other literature, and only the studies that used the same database are included to draw a more accurate and credible conclusion. It is found that the effectiveness of proposed method is verified by comparing the performance of classification problems as addressed by other researchers. As is listed in Table 5, the accuracy of Case 5 is 0.4% different from the best result by Das *et al.* [38] based on normal inverse Gaussian (NIG) parameters in the dual-tree complex wavelet transform (DT-CWT) domain, while Case 7 is just 0.67% less than the best result obtained by the same work. For most of existing methods, the results vary greatly once the classification problems are changed. And the proposed method provides consistent cases-wise performance in a range of 99.33%-100%, while the other techniques show fluctuating results in cases-wise performance. For Case 8, the classification accuracy achieved in this paper is more close to clinic needs, which is significantly higher than that of other well-known works. Therefore, the present model has provided prominent and satisfied performance in dealing with both two-class and three-class classification problems.

As expected, our proposed scheme have outperformed the other models in terms of robustness and stability. Although the concept of image processing has been introduced by literature in [47], [48] for the purpose of epileptic EEG signal classification, but none of them used phase information, multi-scale blocking and quadratic feature selection for further improvement of the classification accuracy. In Fu *et al.*'s method [47], the Hilbert-Huang transform based TFR has been considered as TFI. In literature [48], the energy image obtained from the spectrogram of SFTF was used as TFI. Previous studies [25], [26] had adopted textural features for the classification of epileptic EEG signals. Despite the good performance, the above approaches were focused on just one classification problem. This study has put forward a new model based on 2D-TFI representation, which is different from the approaches presented in the previous researches. STFT is used to derive the time-frequency domain properties of EEG, which is the basis of TFR. TFI techniques can then be

TABLE 5. Performance comparison with the other existing methods employing the same database.

Authors	A/E	B/E	C/E	D/E	ABCD/E	AB/CDE	A/D/E	AB/CD/E
Jaiswal et al. [37]	100	99.50	99.50	95.50	97.60	/	97.20	97.43
Das et al. [38]	100	/	100	/	100	/	100	98.62
Kaya et al. [39]	99.50	/	/	99.50	/	95.40	95.67	/
Jaiswal et al. [40]	100	99.0	97.50	99.0	98.60	/	98.0	/
Bhattacharyya et al. [41]	100	100	99.50	98.0	99.0	/	/	98.60
Zhang et al. [42]	100	/	/	98.10	98.87	/	98.47	98.40
Li et al. [43]	100	/	/	/	99.10	98.48	/	98.10
Orhan et al. [44]	100	/	/	/	99.60	98.80	96.67	95.60
Raiz et al. [45]	98.0	/	/	93.0	96.0	/	84%	82.5%
Mursalin et al. [46]	100	98.0	99.0	98.50	97.40	/	/	/
Proposed method	100	100	100	100	99.60	99.80	99.33	99.60

adapted to enhance the quality of TFR in order to better represent the time-frequency features which characterize different abnormalities. And the amplitude image and phase image are plotted as the objects for LBP. By this way, features extracted from blocks in pixel domain contains both time-frequency information and local texture information. A quadratic feature selection method called KECA-KW is introduced to reduce the dimensions. KW just makes up the shortcoming of the KECA and avoid the omission of PC which is of small contribution rate but of high discrimination. KECA can remove the redundant information caused by the multi-scale blocking LBP features. Hence, the fusion of KECA and KW can make remedies to the disadvantages of both methods and play an crucial role in improving the overall performance of the proposed model. The proposed detection model is reasonable and effective in theory and this proved to be the case. The main contribution of this work lies on:

(a) Instead of using one kind of TFI directly, we investigates two matrices of amplitude coefficients and phase coefficients in STFT domain for TFI plotting. The fusion of amplitude image and phase image can reveal more comprehensive and transient information hidden in EEG, which lays the solid foundations for further realization of the representation of EEG with different classification purposes.

(b) Another salient point of the research is that the idea of multi-scale blocking is exploited for image segmentation. In this regard, the TFI is divided into some sub-blocks not only corresponding to the rhythms of EEG signals but also different time periods. By this way, texture features localized in both global regions and local regions have resulted in significant improvement on classification accuracy.

(c) In this paper, the feature extraction problem explores not just how to obtain the discerning features, but how to remove the redundant ones from the original feature set. By presenting a novel approach for feature extraction based on KECA-KW, this paper breaks through the traditional algorithm framework based on independent PCA. To our best knowledge, there is no such method developed yet, in which the integration of KECA and KW is developed for the processing of EEG signals. KW just makes up the shortcoming of the KECA and avoid the omission of PC which is of small contribution rate but of high discrimination. KECA can reduce the redundant of inner classes which KW can not. Hence, this proposed quadratic feature selection method has shown more hopeful prospects on this issue.

Generally, the algorithm is robust and computationally simple, which has been proven to be highly promising and contributing in the detection of seizures. Moreover, design idea and frame expressed in this paper has have certain theoretical guidance meaning and practical reference value for the research of brain science. We will drill down further and explore deep learning [49]–[51] in our follow-on works.

VIII. CONCLUSION

The automatic seizure detection in EEG is essential in clinical application. In this work, a novel model based on 2D-TFI representation and blocked texture features is proposed in this field. The main purpose of our study has been to develop a suitable scheme for informative feature description. In this regard, we introduce image processing in EEG analysis by means of STFT to transform one-dimensional EEG to multi-dimensional matrix. TFI techniques are adapted to enhance the quality of TFR in order to better represent the time-frequency features which characterize different abnormalities. Additionally, LBP based on multi-scale blocking image is explored to extract the global and local features of EEG signals. The dimension of original features is greatly reduced by a novel feature selection method, namely KECA-KW, which can select features that best describe the behaviour of EEG signals. To be rigorous, eight clinical cases are considered to verify the effectiveness and feasibility of this algorithm. Comparable results achieved with the proposed approach are 100%, 100%, 100%, 100%, 99.60%, 99.80%, 99.33% and 99.60% for Cases 1-8, respectively. The promising results have indicated the outstanding adaptability and stability of this method. We can confirm that the proposed technique has great potentials to be expanded into in clinical development for other conditions, such as brain cognition research, depression diagnosis. As future work, further validation will be proceeded on the proposed method with a large database.

Moreover, we will also commit to the optimization of the algorithm and the corresponding hardware implementations within the system. Building a free-access epileptic EEG database with the cooperation of affiliated hospital of our university is part of the plan.

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