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SCIENTIFIC PAPER

A novel local senary pattern based epilepsy diagnosis system using EEG signals

Turker Tuncer[1] · Sengul Dogan[1] · Erhan Akbal[1]

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Abstract

Epilepsy is a critical and widely seen neurological disorder for people and electroencephalogram (EEG) signals are used to diagnose epilepsy. To accurately diagnose epilepsy, distinctive features of the EEG signals should be extracted. Therefore, a novel texture descriptor is presented for distinctive feature extraction in this study and an EEG recognition method is proposed. The proposed method consists of four main phases. These are feature extraction, feature concatenation, feature reduction and classification. Firstly, the EEG signal is divided into 1×25 size of overlapping blocks and these blocks are converted to 2 dimensional blocks with size of 5×5. Because, the proposed novel local senary pattern (LSP) uses 5×5 size of blocks for feature extraction. 1536 Features are extracted using the proposed LSP. The proposed LSP is used ternary function to extract features and as we know that the main problem of the ternary function is to find optimal threshold value. Therefore, we used 10 threshold values by using standard deviation function and $1536\times10=15{,}360$ features are extracted from an EEG signal. In the feature combining phase, these features are concatenated. In order to reduce these features, a neighborhood component analysis based feature reduction method is used. In the classification phase support vector machine, k nearest neighborhood, quadratic discriminant analysis and linear discriminant analysis are utilized as the classifiers. To test success of the proposed method, the widely used EEG signals dataset which is Bonn University EEG database is used and 7 cases are defined for testing using this database and the proposed method achieved 93.0% classification accuracy for 5 classes case. The obtained results and comparisons clearly indicated success of the proposed LSP based method.

Keywords Local senary pattern · EEG · Epilepsy diagnosis · Feature extraction

Introduction

Epilepsy is one of the major neurologic disease affecting people's life standard. Approximately 2 million people are diagnosed with epilepsy every year worldwide [1, 2]. The disease demonstrates itself in the form of unconscious body movements, convulsions and seizures due to abnormal signal states of brain cells. This disease is caused by excessive electrical discharges of brain cells in a particular region. Patients experience various symptoms during seizures depending on the location and degree of affected brain tissue. Patients with epileptic seizures may experience adverse physical, psychological and social consequences such as loss of consciousness, injury and sudden death [3]. Therefore, methods developed for the diagnosis and treatment of epileptic seizures are of great importance [4–6].

Electroencephalogram (EEG) is a test in which the electrical behavior of the brain is recorded as a signal. Neurons in the brain communicate with each other through electrical stimuli [7]. The EEG test helps to identify problems with this communication. The test monitors and records brain wave signals [8]. The electrodes are connected to the scalp with wires to analyze electrical stimuli in the brain. EEG data contains important information for the diagnosis of epilepsy [9]. EEG signals contain many components. Therefore, the process of examination and diagnosis is time-consuming and costly. There are many studies on automatic diagnostic systems to enable the diagnostic process to be performed more quickly and accurately. Automatic diagnostic systems

✉ Sengul Dogan
sdogan@firat.edu.tr

Turker Tuncer
turkertuncer@firat.edu.tr

Erhan Akbal
erhanakbal@firat.edu.tr

1 Department of Digital Forensic Engineering, Technology Faculty, Firat University, Elazig, Turkey

aim to produce results from EEG signals using methods such as artificial intelligence, feature extraction, machine learning and statistical methods. Feature extraction based and machine learning based approaches achieve high performance rates in diagnosing [5, 10–13]. Some of the widely used state-of-art methods are given as below.

Kaya et al. [10] have developed an approach to feature inferences of EEG signals by 1D-local binary pattern (LBP) method in their study. In the two-step method, they used machine learning methods to classify features and classify the extracted features. Accurate classification rates were obtained as 91% to 99.5% for the used dataset in their study. Kaya [14] proposed a study on the analysis and determination of the relationship between 1D-LBP and Gray relational analysis (GRA) in 2015. A decision support system for the diagnosis of epilepsy and the analysis of EEG signals has been proposed with the GRA method. In the present study, it has achieved success rate between 96 and 100% by evaluating 2 different classes simultaneously with 1D-LBP + GRA method. Kannathal et al. [15] applied entropy based prediction algorithms to the EEG data obtained from normal and epilepsy patients. Using t-test method, 95% of normal and epileptic data can be separated from each other showed. ANFIS was used as a classifier and classification accuracy was found as 90%. Subaşı [16] proposed a model discrete wavelet transform (DWT) and mixture model in the classification of EEG signals. The EEG signals were divided into frequency bands using DWT and these sub-bands were used as inputs to the Mixture of Expert (ME) network. Thus, it was aimed to distinguish between normal and epileptic data. Performance rates were obtained as 93.2% to 94.5% for only two class data. Guler and Übeyli [17] proposed a new model based on neuro-fuzzy interface system to detect electrocardiographic changes in epilepsy patients. In the two-stage decision system, features were extracted using wavelet transform and the system was trained with a backpropagation gradient descent model. As a result, it was ensured that electrocardiogram (ECG) data were differentiated from normal heart rate and partial epilepsy. A performance rate achieved as 98.13% for 2 classes. Kumar et al. [18] using artificial neural network classifiers to detect epileptic seizures has proposed an entropy-based model. In this study, wavelet entropy, sample entropy and spectral entopic of normal and epileptic EEG data were used and feature extraction was performed using recurrent Elman network and radial basis network. In the detection of epileptic seizures for 2 classes, a performance was calculated as 94.5% to 99.75%. Nigam and Graupe [19] presented a neural network based model for the detection of epilepsy. In this study, a multistage nonlinear pre-processing filter in combination with a diagnostic and artificial neural networks were used together. An accuracy rate of 97.2% was obtained for 2 classes with the proposed method for automatic detection of epileptic seizures. Orhan et al. [20] used K-means classifier and multi-layer perceptron neural network for the classification of EEG signals. EEG signals were divided into sub-bands by using DWT and they used K-means method for classification. However, they used two or three classes to obtain numerical results. Yang Li et al. presented a multiscale radial basis function (MRBF) networks and the Fisher vector encoding based epilepsy seizure detection method. Support vector machine (SVM) was chosen as classifier. In their study, two different data sets were tested for a total of eight different classification cases and the obtained results were comparatively results [21]. Ghayab et al. used tunable Q-factor wavelet transform (TQWT) and a statistical approach together to detect brain disease from EEG signals. Firstly, they used TQWT to obtain sub-band frequency coefficients. Then, statistical features were extracted. In their work, bagged tree, k nearest neighbor (KNN), and SVM were utilized as classifier. In the study, tests were performed on the databases of the University of Bonn and Born [22]. Arunkumar et al. examined regional epilepsy to describe the occurrence of different types of diseases. The used focal and non-focal EEG signals were acquired from variable parts of the brain. In the feature extraction phase, the entropy based statistical features. The used entropies are Approximate, Sample and Reyni's entropies. In the classification phase, they used five different classifiers to create five cases. They tested their presented method by using Bern dataset [23]. Oliva et al. proposed an intelligent report software based on machine learning. In order to train the proposed tool, they used Bonn EEG dataset and approximately 84.0% accuracy rate was calculated [24]. Hussein et al. suggested a deep neural network-based approach to epilepsy detection. In the three-tier architecture, a deep long short-term memory network was used to identify different EEG samples. In the next step, the fully connected layer was used to detect areas of the epilepsy in the signal, and finally the softmax layer was used to separate the signals. 94% performance results were obtained for 5 classes [25].Gupta and Pachori proposed multiscale Renyi permutation entropy and Fourier–Bessel series expansion based stable feature extraction method. The extracted features were classified using random forest, least squares SVM and regression. In the tests conducted on the Born database, the performance results were obtained between 93.3 and 99% for 3 different classes [26].

The main problem of the literature is to use two or three classes for epilepsy identification. In this work, we used five classes. A novel texture descriptor is presented for 1D signals. The proposed descriptor uses 5×5 size of block to create six feature values. In the classification phase, SVM, KNN, quadratic discriminant analysis (QDA) and linear discriminant analysis (LDA) classifiers are used. The major contributions of the proposed method are given as below.

- EEG signal recognition is a difficult problem for machine learning. In order to solve this problem, LBP [14] and ternary pattern (TP) [6] are utilized as feature extractor for EEG signal identification. However, these descriptors are not achieved high classification accuracy for five classes. Therefore, we proposed a novel local senary pattern (LSP) to recognize EEG signals with high accuracy.
- LSP uses TP for binary feature extraction. The main problem of the TP is to set threshold value. To solve this problem, a novel multi threshold strategy is presented. The proposed strategy uses 10 threshold values and these values are calculated using standard deviation of the EEG signals and multipliers.
- To evaluate success of the proposed methods, four classifiers are used and the results are compared to other EEG recognition methods. The results proved the success of the proposed LSP.
- The proposed descriptor can be used both signals and images. In this work, we showed success of a novel descriptor for the EEG signals.

Materials

In order to test performance of the proposed LSP based method, Bonn University EEG dataset was used. There are five different classes in this dataset. The used EEG signals has 23.6 s long with 173.61 Hz. The characteristics of these signals are given as follows. The used classes are named as A, B, C, D and E. EEG signals of the A and B classes represent healthy subjects. EEG signal of the A class were recorded when eyes were opened and signals of the B class were recorded when eyes closed. C, D and E classes were recorded before epileptic attack, epileptic zone and during epilepsy attack respectively. Each class has 100 EEG signal [27].

The proposed method

In this study, a novel textural feature extraction method is presented. The proposed LSP uses 5×5 sized block with ternary function. As we know from the literature, the widely used textural feature extractor is LBP and it uses 3×3 sized block because 3×3 sized block is basic neighborhood block. In here, 5×5 sized block is used for deeply feature extraction. However, the size of the block is directly depended on computational complexity. If, we choose 10×10 sized block, the size of feature and computational complexity will increase. Therefore, we selected 5×5 sized block and to clearly mention the proposed method, the used 5×5 sized block is divided into sub-parts and these are called as diagonal, vertical T and horizontal T respectively. Graphical outline of the proposed LSP is shown in Fig. 1.

In the LSP, the 5×5 sized block is divided into three parts and these parts are showed using green, blue and yellow background colors respectively. These parts are called as diagonal, vertical T and horizontal T respectively. The values of these parts and center pixel are used to calculate feature values of the block and 6 feature values are extracted using ternary function. Mathematical description of the TP is given in Eqs. 1 and 2.

$$bit^{upper} = \begin{cases} 1, & p_i - p_c > t, \\ 0, & Otherwise, \end{cases} \tag{1}$$

$$bit^{lower} = \begin{cases} 1, & p_i - p_c < -t, \\ 0, & Otherwise, \end{cases} \tag{2}$$

where bit^{upper} is upper bit, bit^{lower} represents lower bit, t is threshold value, p_i describes ith pixel of the block and p_c is center pixel of the block. The extracted lower and upper bits are used to calculate decimal values. To calculate threshold values, we used a standard deviation based threshold value calculation strategy like Kaya and Ertugrul's method [6]. We select multipliers as 0.1, 0.2,…,1 to calculate optimal threshold. By using this strategy, 15,360 features are extracted because 10 standard deviation based threshold values are used for feature extraction.

$$t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(signal_i - \overline{signal}\right)^2} \times k, \quad k = \{0.1,\ 0.2, \dots, 1\}, \tag{3}$$

where $signal$ is EEG signal, $\overline{signal}$ is average value of the signal and k is multiplier value.

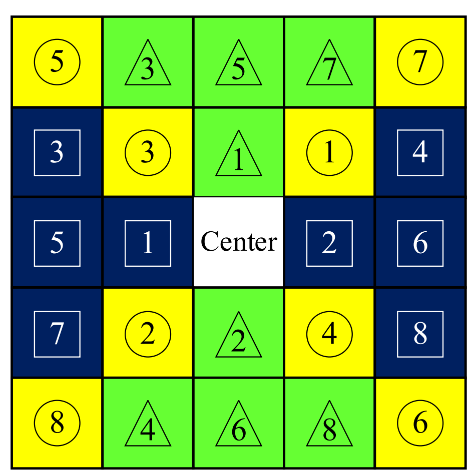


Fig. 1 The block diagram of the proposed LSP using 5×5 sized block

LSP is a LBP like feature extractor. In these descriptors, histograms of the feature signals are utilized as feature vector. The mathematical notation of the LSP is given as below.

Diagonal feature extraction

These features are extracted by using yellow pixels which are shown in Fig. 1.

$$tv^{diagonal}(1) = ter(block(2,\ 4),\ block(3,\ 3),\ t), \tag{4}$$

$$tv^{diagonal}(2) = ter(block(4,\ 2),\ block(3,\ 3),\ t), \tag{5}$$

$$tv^{diagonal}(3) = ter(block(2,\ 2),\ block(3,\ 3),\ t), \tag{6}$$

$$tv^{diagonal}(4) = ter(block(4,\ 4),\ block(3,\ 3),\ t), \tag{7}$$

$$tv^{diagonal}(5) = ter(block(1,\ 1),\ block(3,\ 3),\ t), \tag{8}$$

$$tv^{diagonal}(6) = ter(block(5,\ 5),\ block(3,\ 3),\ t), \tag{9}$$

$$tv^{diagonal}(7) = ter(block(1,\ 5),\ block(3,\ 3),\ t), \tag{10}$$

$$tv^{diagonal}(8) = ter(block(5,\ 1),\ block(3,\ 3),\ t). \tag{11}$$

Vertical T feature extraction

In Fig. 1, the vertical T pixels are shown using green background.

$$tv^{verticalT}(1) = ter(block(2,\ 3),\ block(3,\ 3),\ t), \tag{12}$$

$$tv^{verticalT}(2) = ter(block(4,\ 3),\ block(3,\ 3),\ t), \tag{13}$$

$$tv^{verticalT}(3) = ter(block(1,\ 2),\ block(3,\ 3),\ t), \tag{14}$$

$$tv^{verticalT}(4) = ter(block(5,\ 2),\ block(3,\ 3),\ t), \tag{15}$$

$$tv^{verticalT}(5) = ter(block(1,\ 3),\ block(3,\ 3),\ t), \tag{16}$$

$$tv^{verticalT}(6) = ter(block(5,\ 3),\ block(3,\ 3),\ t), \tag{17}$$

$$tv^{verticalT}(7) = ter(block(1,\ 4),\ block(3,\ 3),\ t), \tag{18}$$

$$tv^{verticalT}(8) = ter(block(5,\ 4),\ block(3,\ 3),\ t). \tag{19}$$

Horizontal T feature extraction

In the Fig. 1, blue pixels are used to extract horizontal T features.

$$tv^{horizontalT}(1) = ter(block(3,\ 2),\ block(3,\ 3),\ t), \tag{20}$$

$$tv^{horizontalT}(2) = ter(block(3,\ 4),\ block(3,\ 3),\ t), \tag{21}$$

$$tv^{horizontalT}(3) = ter(block(2,\ 1),\ block(3,\ 3),\ t), \tag{22}$$

$$tv^{horizontalT}(4) = ter(block(2,\ 5),\ block(3,\ 3),\ t), \tag{23}$$

$$tv^{horizontalT}(5) = ter(block(3,\ 1),\ block(3,\ 3),\ t), \tag{24}$$

$$tv^{horizontalT}(6) = ter(block(3,\ 5),\ block(3,\ 3),\ t), \tag{25}$$

$$tv^{horizontalT}(7) = ter(block(4,\ 1),\ block(3,\ 3),\ t), \tag{26}$$

$$tv^{horizontalT}(8) = ter(block(4,\ 5),\ block(3,\ 3),\ t), \tag{27}$$

where $ter(.,.,.)$ is ternary function, $block$ is 5×5 sized block. $tv^{diagonal}$, $tv^{verticalT}$ and $tv^{horizontalT}$ are diagonal, vertical T and horizontal T ternary values of the block respectively. In order to extract bits, Eqs. 1 and 2 are used and 8×6 bits are extracted. To better understand the proposed LSP, a numerical example is shown in Fig. 2.

As shown in Fig. 2, the proposed LSP extracts six 8-bits values. By using these values, six feature images are constructed and histograms of these images are utilized as feature. A 8-bit image has $2^8 = 256$ histogram values. Therefore, 256 features are extracted from each constructed image. The block diagram of the proposed method is given in Fig. 3.

As seen in Fig. 3, the proposed method consists of LSP transformation, feature signal construction, histogram extraction, histogram concatenation, feature reduction and classification phases. Firstly, LSP is applied to 1D signal and six feature signals are constructed. Then, histograms of

Fig. 2 An example about the proposed LSP

t=20

340	353	400	470	538
-351	-143	22	146	213
294	326	350	380	402
524	361	58	-475	-910
-393	-293	-147	68	300

Upper diagonal value $(00000010)_2 = 2$

Lower diagonal value $(10110101)_2 = 181$

Upper vertical T value $(00001010)_2 = 10$

Lower vertical T value $(11010110)_2 = 214$

Upper horizontal T value $(01000110)_2 = 70$

Lower horizontal T value $(10111001)_2 = 185$

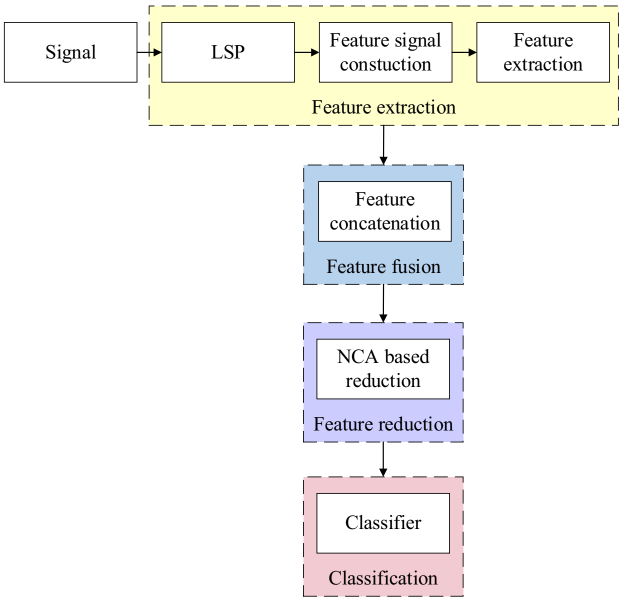


Fig. 3 Block diagram of the proposed LSP based 1D signal recognition method

the calculated components are extracted. Histogram of each component is concatenated to obtain 1536 × 10 = 15,360 features. To reduce the dimension of the concatenated features, a neighborhood component analysis (NCA) based feature reduction method is considered. By using NCA based method, features are reduced from 15,360 to 256. In this method, the concatenated features are divided into 60 sized non-overlapping windows and NCA is utilized as weight generator. NCA is one of the frequently used feature selector in the literature. To select distinctive ones, NCA generates non-negative weights using distance metric as 1NN. The most important attribute of the NCA is to generate non-negative weights. By using these weights, a weighted average calculation based feature reduction is proposed. Mathematical notation of the NCA based feature are given as Eqs. 28–29 [28, 29].

$$w = NCA(feat,\ target), \tag{28}$$

$$feat^{final}(k) = \frac{\sum_{a=1}^{60} w(a) * feat(a)}{\sum_{a=1}^{60} w(a)}, \quad k = \{1,\ 2, \ldots, 256\}. \tag{29}$$

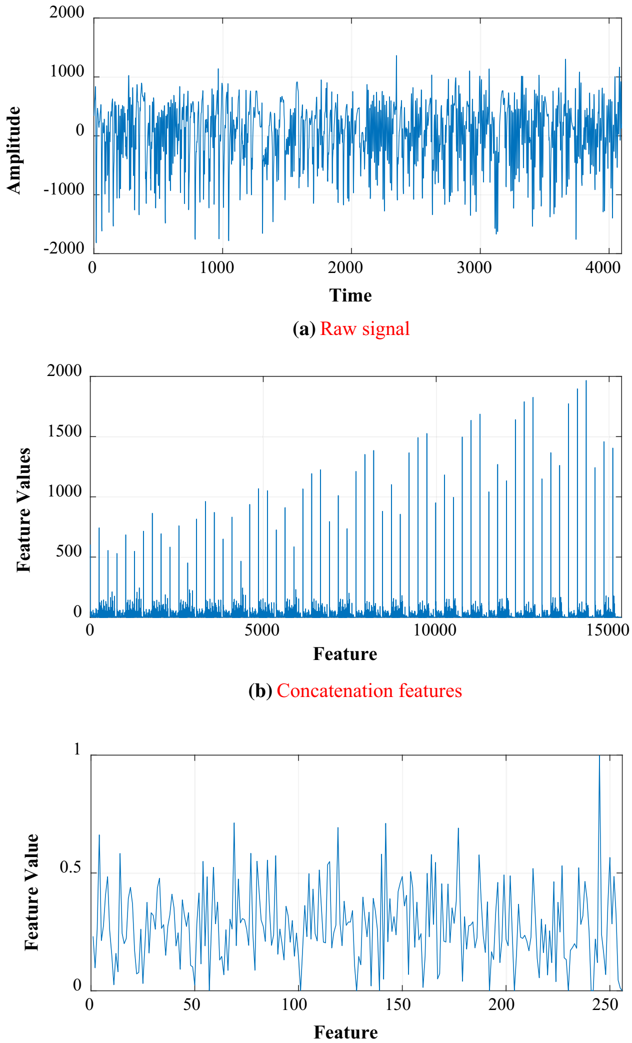
As we know that, the EEGs are 1 dimensional signals. However, the proposed LSP is a 2D texture descriptor. 1D signal is divided into 1 × 25 size of windows and these windows are converted into 5 × 5 size of matrix. Then, the proposed LSP is applied onto the blocks with size of 5 × 5. The calculated feature values which are upper and lower diagonal, vertical T and horizontal values are used to construct six feature signals. Histograms of these signals are concatenated to obtain feature vector of the EEG signals. Also, 10 threshold values are used and 15,360 features are extracted. These features are reduced 256 using NCA based feature reduction and 4 classifiers are used to test the proposed LSP based method. The pseudo code of this method is given in the Algorithm 1.

Algorithm 1. Pseudo code of the proposed LSP based EEG signal recognition method.

Input: EEG signal E with size of L

Output: Feature (*f*) with size of 256.

1: Load E.
2: for i=1 to L-24 do
3: window=E(i:i+24); // Construct 25 size of overlapping window.
4: block=reshape(window, 5 x 5); // Reshape window to 5 x 5 size of block.
5: Assign center, diagonal, vertical T and horizontal T values.
6: **for** j=1 to 10 **do**
7: $H^j = LSP\left(block, \frac{j}{10}\right)$; // $\frac{j}{10}$ is threshold value of the LSP. LSP extract 1536 features in each loop.
8: **end for j**
9: **end for i**
10: Concatenate extracted histograms and obtain 15360 features.
11: Reduce feature sizes from 15360 to 256 using Eqs. 4-5. and obtain f
12: Forward f to classifiers to obtain numerical training and testing results.



(a) Raw signal

(b) Concatenation features

(c) Reduced features

Fig. 4 Graphical outline of the proposed LSP based feature extraction using a sample EEG signal

A graphical example about the proposed LSP based feature extraction method is shown in Fig. 4.

As shown in Fig. 4, 15,360 features are extracted from an EEG signal, these features are reduced to 256 features by using NCA based reduction method. 256 Features are used to compare the other methods for instance LBP and TP. The extracted features are forwarded to classifiers. To evaluate performance of the proposed method, LDA [11], QDA [30], SVM [11] and KNN [31] classifiers are used. In the SVM, cubic kernel SVM is used and Euclidean distance based KNN was considered. The attributes of the used classifiers are given as follows. LDA and QDA are non-parametric classifier and these are quadratic and linear classifiers. In the KNN, K was selected as 1 and distance metric was Euclidean distance. A polynomial SVM was also used. It has third degree polynomial activation function. Therefore, it is called as cubic SVM. Multiclass metric of it one versus one. Box constraint level is 1 and kernel scale mode is auto.

The comprehensively results are given in the "Results" and "Discussion" section.

Table 1 Recognition rates (%) of the proposed LSP using LDA, QDA, SVM and KNN with tenfold cross validation

Case	Performance metric	LDA	QDA	SVM	KNN
A–E	Accuracy	91.5	91.5	**99.5**	97.5
	Sensitivity	90.0	91.0	**100.0**	98.0
	Specificity	93.0	92.0	**99.0**	97.0
A–D	Accuracy	92.5	91.5	**99.5**	**99.5**
	Sensitivity	89.0	92.0	99.0	**100.0**
	Specificity	96.0	91.0	**100.0**	99.0
B–E	Accuracy	91.0	92.0	96.5	**97.0**
	Sensitivity	94.0	95.0	96.0	**99.0**
	Specificity	86.0	89.0	**97.0**	95.0
D–E	Accuracy	81.5	89.0	**100.0**	98.5
	Sensitivity	86.0	92.0	**100.0**	99.0
	Specificity	77.0	86.0	**100.0**	98.0
C–E	Accuracy	94.5	95.0	**100.0**	99.5
	Sensitivity	97.0	99.0	**100.0**	**100.0**
	Specificity	92.0	91.0	**100.0**	99.0
A–D–E	Accuracy	84.67	89.0	**98.67**	96.33
	Sensitivity	80.0	87.0	**100.0**	95.0
	Specificity	87.0	90.0	**98.0**	97.0
A–B–C–D–E	Accuracy	78.0	75.0	**93.0**	89.2
	Sensitivity	79.0	58.0	**97.0**	88.0
	Specificity	77.75	79.25	**92.0**	89.5

The bold values are represented the best values

Results

In this section, test results of the proposed method are evaluated. To simulate the proposed method, we used MATLAB 2016a programming environment on a personal computer (PC). The used PC has 16 gigabytes RAM, Intel i7-7700 3.20 GHz microprocessor and Windows 10.1 Ultimate operating system. MATLAB Classification Learner tool was used for classification and tenfold cross validation was also chosen to obtain numerical results. We used accuracy, sensitivity and specificity metrics. In the literature, different cases of the Bonn EEG dataset have been used for testing. The widely used cases are A–E, A–D, B–E, D–E, C–E, A–D–E [6, 14–16, 18–20, 35–38]. Also, we used A–B–C–D–E classes are utilized as case. In order to evaluate performance of the proposed accuracy, sensitivity, specificity and geometric mean performance evaluation metrics were used and the mathematical notation of them are given in Eqs. 30–33 [32–34].

$$Acc\ (\%) = \frac{\#\ True\ predictive\ samples}{\#\ Total\ number\ of\ samples} \times 100, \tag{30}$$

Table 2 Performance comparison of the proposed LSP–SVM models

Reference	Method	Classes	Accuracy (%)
[6]	Kaya and Ertugrul's method (2018)	A–E	**100.0**
		A–D	**100.0**
		B–E	**97.50**
		D–E	94.50
		C–E	97.50
		A–D–E	95.70
[14]	Kaya's method (2015)	A–E	**100.0**
		B–E	96.00
		C–E	**100.0**
		D–E	99.00
		A–D	**100.0**
[15]	Kannathal et al.'s method (2005)	C–E	99.00
		D–E	97.00
		C–D–E	97.67
[16]	Subasi's method (2007)	A–E	94.50
[18]	Kumar et al.'s method (2010)	A–E	**100.0**
		A–D–E	99.28
[19]	Nigam and Graupe's method (2004)	A–E	97.20
[20]	Orhan et al.'s method (2011)	A–E	**100.0**
[35]	Kaya et al.'s method (2014)	A–E	99.50
		A–D	99.50
		D–E	95.50
		E–CD	97.00
		AB–CDE	93.00
		A–D–E	95.67
[37]	Srinivasan et al.'s method (2005)	A–E	99.60
[37]	Fathima et al.'s method (2011)	A–E	99.75
[38]	Guo et al.'s method (2010)	A–E	99.85
LSP + SVM		A–E	99.50
		A–D	99.50
		B–E	96.50
		D–E	**100.0**
		C–E	**100.0**
		A–D–E	**98.67**
		A–B–C–D–E	**93.0**

The bold values are represented the best values

$$Sen\ (\%) = \frac{TP}{TP + FN} \times 100, \quad (31)$$

$$Spe\ (\%) = \frac{TN}{TN + FP} \times 100, \quad (32)$$

$$gm\ (\%) = \sqrt{Spe \times Sen} \times 100, \quad (33)$$

where Acc is accuracy, Sen is sensitivity, Spe is specificity and gm describes geometric mean. TP, TN, FP and FN are true positives, true negatives, false positives and false negatives respectively.

The accuracy, sensitivity and specificity results of the proposed LSP base method are shown as Table 1 for each case.

Previously presented EEG classification methods were used to obtain comparison results. In the Table 2, the accuracy rates of the proposed method and previously presented methods are listed. The best results of the previously presented methods were given from [6].

As seen in Table 2, the selected state-of-art methods did not use A–B–C–D–E case. Also, the proposed LSP is a textural descriptor. Therefore, 1D-LBP and 1D-TP based methods were selected for A–B–C–D–E comparison. The

Table 3 Comparisons of the 1D-TP, 1D-LBP and the proposed method using LDA, QDA, SVM and KNN classifiers for A–B–C–D–E classes

Method	Classifier	Sen (%)	Spe (%)	gm (%)	Acc (%)
1D-LBP (256 features)	KNN	67.0	67.75	67.37	67.60
	SVM	88.0	67.75	77.21	71.80
	LDA	58.0	59.75	58.87	59.40
	QDA	74.0	60.0	66.63	62.80
1D-TP upper (256 features)	KNN	60.0	72.5	65.95	70.0
	SVM	87.0	74.75	80.64	77.20
	LDA	60.0	64.25	62.09	64.40
	QDA	62.0	58.75	60.35	59.60
1D-TP lower (256 features)	KNN	62.0	68.50	65.17	67.20
	SVM	81.0	73.75	77.29	75.20
	LDA	70.0	58.50	63.94	60.80
	QDA	70.0	57.0	63.17	59.40
LSP (256 features)	KNN	88.0	89.50	88.75	89.20
	SVM	**97.0**	**92.0**	**94.47**	**93.0**
	LDA	79.0	77.75	78.37	78.0
	QDA	58.0	79.25	67.80	75.0

The bold values are represented the best values

comparatively results of them and the proposed method using KNN, SVM, LDA and QDA are given in Table 3.

The space complexity of the proposed method is calculated using big O notation given as below.

The complexity of the feature extraction using LSP is calculated as $O(60n)$. Because the proposed LSP extracts 6 feature images 10 times by using 10 threshold values, where n is length of the used EEG signal.

In the classification phase, tenfold cross validation is used. Hence, the space complexity of it is calculated as $O(10\ k)$ where k represents onefold training.

The computational complexity of the proposed LSP based method is calculated as $O(60n+10\ k)$.

Discussions

The discussions are given as follows. To solve threshold value problem, a multiple threshold values strategy was presented and deeply features were extracted using this strategy. 5 EEG cases were used to test performance of the proposed method. In the literature, generally two or three classes were used to evaluation. Also, four classification methods were utilized as classifier. The results clearly illustrated that the proposed LSP based method achieved satisfactory results for EEG signal recognition. The best recognition rate is calculated as 93.0% for A–B–C–D–E classes using SVM classifier. Also, 6 cases (A–E, A–D, B–E, D–E, C–E and A–D–E) are used and the best recognition rates of them were calculated as 99.5%, 99.5%, 97.0%, 100.0%, 100.0% and 98.67% respectively. The proposed LSP is deeply extracted distinctive features of the EEG signals. To better understand success of the proposed method, the widely used method are used for comparisons and their results were listed in Tables 2 and 3. The comparisons clearly showed that the proposed method achieved best recognition rates for C–E, D–E, A–D–E and A–B–C–D–E among all of them. The proposed method is a cognitive method, because any optimization or weight updating method are not used. To apply the proposed method is simple because it has a simple mathematical background. The space complexity of this method is calculated as approximately $O(n)$. This calculation clearly showed that the proposed LBP based EEG signal recognition method has low space complexity. The advantages of the proposed method are listed in below.

- The classification of the Bonn dataset EEG signals in five classes is very hard problem. The proposed method solves this problem and it achieved 93.0% classification accuracy for 5 clusters classification.
- The proposed method is a cognitive method. Any metaheuristic optimization method is not used to increase classification accuracy in this method.
- A lightweight method is presented.
- The proposed method is an extensive signal processing method. It can be applied other biomedical signal such as ECG and voices of the patients.

The limitation of the proposed method is to use small dataset.

Conclusions

In this work, a novel LSP is proposed to extract stable features from EEG signals. The proposed LSP is inspired of the chess game. To create patterns of the LSP, diagonal, vertical T and horizontal T patterns are used. Features are extracted using LSP. LSP uses ternary function to extract binary features. To solve threshold value problem of the ternary function, a standard deviation based strategy is used. 15,360 Features are extracted by using 10 threshold values. To reduce thee features, NCA based feature reduction method is used and 256 features are obtained. The widely used EEG signals are considered to test recognition rate of this method. The best accuracy rates were calculated as 99.50%, 99.50%, 97.00%, 100.0%, 100.0%, 98.67% and 93.0% for A–E, A–D, B–E, D–E, C–E, A–D–E and A–B–C–D–E classes. The proposed method was also compared to the previously presented state-of-art methods. The best recognition rates of the were achieved for D–E, C–E, A–D–E and A–B–C–D–E classes among all of them. The results and comparisons clearly illustrated that the proposed LSP based method is a distinctive feature extraction method among the used state-of-art methods and the results also indicated that an intelligent system can be constructed by using the proposed method.

The proposed LSP based method is a general learning methods for signals. Therefore, the proposed LSP can be applied the other signals such as ECG, EMG, voices in the future works. A novel cloud based online epilepsy monitoring, detection, tracking and reporting system can be developed using IOT and the proposed method. A novel LSP based deep learning network can also be presented in the future.

Compliance with ethical standards

Conflict of interest There is no 'Conflict of Interest' in the publication of the manuscript "A novel ternary chess pattern based epilepsy diagnosis system using EEG signals".

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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