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One-dimensional Center Symmetric Local Binary Pattern Based Epilepsy Detection Method

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Abstract: The diagnosis of epilepsy from the EEG signals is determined by the visual/manual evaluation performed by the neurologist. This evaluation process is laborious and evaluation results vary according to the experience level of neurologists. Therefore, automated systems that will be created using advanced signal processing techniques are important for diagnosis. In this study, a new feature extraction method is proposed using multiple kernel based one-dimensional center symmetric local binary pattern (1D-CSLBP) to identify epileptic seizures. To strengthen this method, levels have been created and multi-level feature extraction has been carried out. Discrete wavelet transform (DWT) was used to generate the levels and feature extraction was performed using the low pass filter coefficient (L bands) obtained at each level. Neighborhood component analysis (NCA) was used to select the most distinctive features. The obtained features are classified using the nearest neighbors (kNN) algorithm. A high performance method was obtained by using multiple kernel NCA and NCA. The 1D-CSLBP and NCA-based method has reached 100.0% accuracy in A-E, A-D-E, D-E, C-E situations.
Keywords: Feature extraction, local feature generation, feature selection, classification.

Tek Boyutlu Merkez Simetrik Yerel İkili Desen Tabanlı Epilepsi Tespit Yöntemi

Öz: EEG sinyallerinden epilepsi tanısı, nörolog tarafından yapılan görsel / manuel değerlendirme ile belirlenir. Bu değerlendirme süreci zahmetlidir ve değerlendirme sonuçları nörologların deneyim düzeyine göre değişir. Bu nedenle gelişmiş sinyal işleme teknikleri kullanılarak oluşturulacak otomatik sistemler tanı için önemlidir. Bu çalışmada, epileptik nöbetleri tanımlamak için çoklu çekirdek tabanlı tek boyutlu merkez simetrik yerel ikili model (1D-CSLBP) kullanılarak yeni bir özellik çıkarma yöntemi önerilmiştir. Bu yöntemi güçlendirmek için seviyeler oluşturulmuş ve çok seviyeli özellik çıkarımı gerçekleştirilmiştir. Seviyeleri oluşturmak için ayrık dalgacık dönüşümü (DWT) kullanılmış ve her seviyede elde edilen düşük geçişli filtre katsayısı (L bantları) kullanılarak özellik çıkarımı gerçekleştirilmiştir. Mahalle bileşen analizi (NCA), en ayırt edici özellikleri seçmek için kullanıldı. Elde edilen özellikler en yakın komşular (kNN) algoritması kullanılarak sınıflandırılır. Çoklu çekirdek NCA ve NCA kullanılarak yüksek performanslı bir yöntem elde edildi. 1D-CSLBP ve NCA tabanlı yöntem, A-E, A-D-E, D-E, C-E durumlarında% 100.0 doğruluğa ulaşmıştır.
Anahtar kelimeler: Özellik çıkarma, yerel özellik üretimi, öznitelik seçimi, sınıflandırma.

1. Introduction

The human brain has a complex structure consisting of billions of neurons and connecting with electrical signals [1-2]. The disease caused by recurrent attacks resulting from abnormal electrical discharges of these neurons is called epilepsy [3,4]. Epilepsy can affect individuals of all ages [5]. According to world health organization [6], It is considered one of the most common brain diseases among neurological disorders [7] [8] and affects approximately 1% of the population worldwide [9,10,11,12]. The number of epilepsy is more pronounced in developing countries [13].

Epileptic seizures are caused by temporary electrical disturbances in the brain [14]. Seizures usually begin with sudden attacks [15]. Diagnosis and monitoring of seizures is done with an electroencephalogram (EEG) signals and EEG signals defined as letter of brain [3]. We can extract more information as to brain using EEG signals [16, 17]. EEG [18] are collected through sensors attached to the scalp or electrodes. EEG signals are often used for the diagnosis of brain-based diseases [1,19-20]. EEG is considered as the most important diagnostic tool for epilepsy [6, 21, 22].

Generally, EEG signals are acquired between two seizures (interictal period) and rarely during one seizure (ictal period) [3]. Epilepsy patients have abnormalities in EEG signals [5,8]. The main feature of epileptic seizures in the EEG signal is the presence of spikes [10].

Epilepsy is usually diagnosed by a neurologist through visual evaluation of EEG signals [23, 24, 25]. Diagnosing epilepsy based on visual inspection of EEG signals is a laborious and lengthy process [3,5,26, 27,28].

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In addition, results of visual analysis performed by different neurologists vary according to the level of experience of physicians [6,20,22,29]. Therefore, methods based on advanced signal processing techniques are important for fast, reliable and automated diagnosis of epilepsy from EEG signals [2,21]. Automatic detection of epileptic seizures can assist neurologists in evaluating long-term EEG recordings [25].

1.2. Literature review

With the development of information technologies, many artificial intelligence, machine learning techniques [8] and advanced digital signal processing methods have been applied [30] to efficiently detect epileptic seizures automatically [5,16,29]. Some of the automated EEG classification

Li et al. [7] presented a new automated seizure detection method based on multiscale radial fundamental function (MRBF) networks and Fisher vector (FV) coding. Jiang et al. [31] used a method for automatic seizure detection that uses features based on symplectic geometry decomposition. Mohammadpoory et al. [32] to be Support Vector Machine (SVM), K-Nearest Neighbor (KNN), Decision Tree (DT) and Naive Bayes (NB) as a classifier with the method based on weighted visibility graph entropy (WVGE) to describe seizure from EEG signals. He used four popular classifiers. Mahmoodiana et al. [33] used an approach based on cross-bispectrum properties to detect epileptic seizures. Yavuz et al. [34] used mel frequency cepstral coefficients (MFCCs) and neural network-based classification method to detect real-time seizures from EEG signals.

Sharma et al. [35] proposed a new semi-precise programming (SDP) formulation without any parameterization to design optimal orthogonal wavelet filter banks (OWFB) for automatic detection of epileptic seizure. Akyol [36] used the stacking unit-based DNN method to address the dual detection problem for epilepsy detection. Yuan et al. [37] used a method based on a weighted over learning machine (ELM) for seizure detection.

Zhou et al. [38] used singular spectrum analysis (SSA), support vector machine (SVM), extreme learning machine (ELM), and artificial neural network (ANN) to classify EEG signals. Yuan et al. [39] proposed a multi-image deep learning model to capture brain abnormality from multichannel epileptic EEG signals for seizure detection. Hossain et al. [40] used a deep CNN model for the task of seizure detection in the EEG epilepsy dataset. Liu et al. [41] used incremental entropy (IncrEn) and boost vector machines (SVMs) for automatic seizure detection in EEG signals. Harender and Sharma [42], Discrete wavelet transform (DWT) and Mean Absolute Value (MA), Standard Deviation (SD) and Mean power (AP), k-Nearest Neighbor (k-NN) classifier for detecting epileptic seizures from EEG signal used. Zhou et al. [43], the convolutional neural network (CNN) method was used to detect epileptic episodes. Li et al. [44] proposed a method for epileptic seizure detection using the CE-stSENet.

1.3. Dataset

The Bonn University Hospital is the commonly used database in the literature [3]. This dataset is named BONN EEG dataset and it was created by Andrzejak et al. [45]. It includes five categories from A to E, each containing 100 single-channel EEG segments with a length of 23.6 seconds duration from five healthy epilepsy patients. A class EEG signals were collected from healthy volunteers with eyes open; B class was collected from healthy volunteers with their eyes closed; C and D classes include seizure-free intervals, and subset E contains EEG signals obtained during active seizure [20].

2. Proposed Method

The main purpose of this study is to obtain high results in the Bonn EEG data set using a new feature extractor. For this purpose, a new feature extraction method using a multi-core one-dimensional central symmetric binary pattern (1D-CSLBP) is proposed. To strengthen this method, levels have been created and multi-level feature extraction has been carried out. Discrete wavelet transform (DWT) was used to generate the levels and feature extraction was performed using the low pass filter coefficient (L bands) obtained at each level. Neighborhood component analysis (NCA) was used to select the most prominent features. The properties obtained are classified using the k nearest neighbor (kNN) algorithm. The block diagram of the proposed method is given in Figure 1.

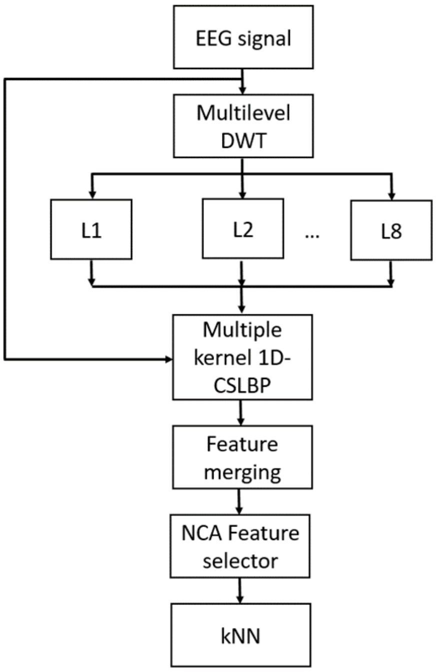

Figure 1. Flowchart of the presented 1D-CSLBP based EEG classification model.

As can be seen Figure 1, the main phases of the proposed method can be listed as follows. (i) 1D-CSLBP and DWT based multi-level feature extraction method, NCA based feature selection and classification. These phases are explained in detail in subsections.

2.1. Feature extraction

Feature generation phase is one of the most important phases of machine learning methods. The stronger and more distinctive the extracted feature, the higher the classification performance is obtained. Feature extraction methods are divided into two: handcrafted feature extraction and deep feature extraction. Manual feature extraction methods, on the other hand, are categorized into two categories: statistics-based and histogram-based (features obtained using descriptors). In this article, a new histogram-based feature extractor is proposed for the extraction of distinctive features, and this feature extractor is called multi-core 1D-CSLBP. Multi-core 1D-CSLBP is used as the key feature extractor of the proposed method. 8-level DWT is used to generate multi-level features. The steps of the recommended feature extraction method are given as follows.

Step 1: By using multilevel DWT, low pass DWT frequency bands are obtained. Here, daubechies 4 (db4) is used as the main wavelet function as DWT filter.

$$[L_1, H_1] = DWT(S) \tag{1}$$

$$[L_i, H_\mathrm{i}] = DWT(L_{i-1}), i = \{2,3, \dots ,8\} \tag{2}$$

In Eqs. 1 and 2, $DWT(.)$ is DWT function, L_i, H_i i$^{\text{th}}$ level low-pass and high-pass filter coefficients and S is the used EEG signal. Eqs. 1 and 2 eight L bands are obtained. The length of each EEG signal used in the Bonn dataset was calculated to be 4097. The number of levels are calculated using $\left[log_2(\frac{4097}{9})\right] = 8$ equation. Herein, 4097 and 9 are defined length of the EEG and length of the used overlapping block respectively.

Step 2: Extract features from S and L vectors using $1DCSLBP$.

$$O^1 = 1DCSLBP(S) \tag{3}$$

$$O^k = 1DCSLBP(L_{k-1}), k = \{2,3, \dots ,9\} \tag{4}$$

Herein, 1*DCSLBP(.)* is used to define 1D-CSLBP. Steps of the 1D-CSLBP are given below.
Step 2.1: Divide the used signal into 9- sized overlapping blocks.

Figure 2. *Graphical demonstration of the used nine sized overlapping window*.
Step 2.2. Extract bits using signum (basic comparison function) and ternary functions.

$$bitS(i) = \begin{cases} 0, s(i) < (s(10-i) \\ 1, s(i) \geq s(10-i) \end{cases}, i = \{1,2,3,4\} \tag{5}$$

$$bitU(i) = \begin{cases} 0, s(i) - s(10-i) \leq d \\ 1, s(i) - s(10-i) > d \end{cases} \tag{6}$$

$$bitL(i) = \begin{cases} 0, s(i) - s(10-i) \geq -d \\ 1, s(i) - s(10-i) < -d \end{cases} \tag{7}$$

Herein, *bitS* is bits calculated using the signum function, *bitUY* is upper ternary bits, *bitL* is lower ternary bits. d is threshold value and it is calculated using Eq. 8.

$$d = \frac{std(S)}{2} \tag{8}$$

where std(.) is standard deviation function.
Step 2.3. Calculate three feature signal using the generated bits.

$$OS^1(k) = \sum_{j=1}^{4} bitS(j) * 2^{j-1}, k = \{1,2, \ldots \ldots, U-8\} \tag{9}$$

$$OS^2(k) = \sum_{j=1}^{4} bitU(j) * 2^{j-1} \tag{10}$$

$$OS^3(k) = \sum_{j=1}^{4} bitL(j) * 2^{j-1} \tag{11}$$

Herein, OS^1,OS^2 and OS^3 are feature vector.
Step 2.4. Extract histograms
Step 2.5. Obtain 48 features by merging the extracted histograms.
Steps 2.1-2.5 are defined the 1DCSLBP feature extraction.
Step 3: Apply 1DCSLBP to generate (X) .

$$X\big((k-1) * 48 + j\big) = O^k(j), k = \{1,2, \ldots \ldots 9\}, j = \{1,2, \ldots .,48\} \tag{12}$$

By applying Eq. 12, 432 size feature is extracted.

2.2. Feature selection

At this stage, the most significant 48 of the 432 features extracted using the NCA method (48 features were selected because multi-core 1D-CSLBP extracted 48 features). NCA is a method similar to the kNN algorithm and the main purpose of this method is to generate weights for each feature. All weights produced using NCA are positive. In this method, initial weights are assigned first. These weights are optimized using stochastic gradient descent (SGD) and a distance-based fitness function. NCA is a simple but effective method. For this reason, the NCA method is one of the methods frequently used in the literature. By using NCA, weights of all features are calculated and ordered indexes of the features are obtained by ordering these weights in descending order. Using these indices, the most significant properties are selected. Feature selection is the 4th step of the proposed method, and this step is as follows.

Step 4: Select the most valuable 48 features deploying NCA.

2.3. Classification

The last step of the proposed method is the classification stage. kNN classifier was used in the classification stage. The properties of the classifier used are as follows.

k: 1,

Distance: Manhattan uzaklığı,

Voting: None

Step 5: Classify 48 features employing kNN.

3. Experimental Results

The Bonn EEG dataset was used to test the performance of the proposed method on EEG signals. The main purposes of using the Bonn EEG dataset are as follows.

- The Bonn dataset is a frequently used dataset in the literature. Therefore, many comparison results can be obtained.
- Using the Bonn dataset, different situations are created and the performances of these situations are tested.

The situations used for tests in this article are as follows.

Table 1. The defined cases using Bonn EEG dataset.

Case	Classes
Case 1	AB-CD-E
Case 2	ABCD-E
Case 3	A-E
Case 4	A-D-E
Case 5	D-E
Case 6	C-E

Performance metrics used to test the situations shown in Table 1 are accuracy, recall, precision and F1-score. The performance metrics obtained according to the situations are given in the table below.

Table 2. Results (%) of the presented model.

Case	Accuracy	Recall	Precision	F1
Case 1	98.60	98.33	98.67	98.50
Case 2	99.60	99.0	99.75	99.37
Case 3	100.0	100.0	100.0	100.0
Case 4	100.0	100.0	100.0	100.0
Case 5	100.0	100.0	100.0	100.0
Case 6	100.0	100.0	100.0	100.0

According to the results in Table 2, the proposed 1D-CSLBP and NCA based method, 3-6. In cases it has reached 100.0% accuracy. A comparison table is given to show the performance of the proposed method and the comparative results are listed in Table 3.

Table 3. Comparatively results (%).

Case	Method	Accuracy (%)
Case 1	Orhan et al. [46]	95.60
	Hassan et al. [47]	97.60
	Our model	**98.60**
Case 2	Orhan et al. [46]	99.60
	Hassan et al. [47]	99.20
	Our model	**99.60**
Case 3	Acharya et al. [48]	98.50
	Hassan et al. [47]	100.0

	Our model	**100.0**
Case 4	Hassan et al. [47]	96.67
	Hassan et al. [47]	98.67
	Our model	**100.0**
Case 5	Kaya et al. [49]	95.50
	Siuly et al. [50]	93.60
	Our model	**100.0**
Case 6	Hassan et al. [47]	99.0
	Our model	**100.0**

As shown in Table 3, the proposed method has the best performance among all methods.

The advantages of the proposed method can be listed as follows.

- By using less number of features, high accuracy is obtained.
- The proposed method is simple and can be easily coded.
- A high performance method has been obtained by using multi-core 1D-CSLBP and NCA. The obtained method has reached high accuracy rates by using a simple classifier such as kNN.
- No optimization algorithm has been used to increase the performance of the method. This situation shows that the method is a cognitive method.

3. Conclusions

This research presents a new 1D-CSLBP and NCA based EEG classification model to detect epileptic seizures automatically. To generate low, medium and high level features, a multilevel feature extraction model is presented by employing 1D-CSLBP and DWT together. NCA is employed to choose the most discriminative features and 48 the most significant features are selected. Six cases are defined to evaluate the presented model. 100.0% accuracies were reached for Cases 4-6. 98.60% and 99.60% accuracies were attained for Cases 1-2. The calculated results, comparisons and findings obviously denoted the success of the presented 1D-CSLBP and NCA based model.

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