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Automatic Identification of Epileptic Seizures From EEG Signals Using Sparse Representation-Based Classification

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ABSTRACT Identifying seizure activities in non-stationary electroencephalography (EEG) is a challenging task since it is time-consuming, burdensome, and dependent on expensive human resources and subject to error and bias. A computerized seizure identification scheme can eradicate the above problems, assist clinicians, and benefit epilepsy research. So far, several attempts were made to develop automatic systems to help neurophysiologists accurately identify epileptic seizures. In this research, a fully automated system is presented to automatically detect the various states of the epileptic seizure. This study is based on sparse representation-based classification (SRC) theory and the proposed dictionary learning using electroencephalogram (EEG) signals. Furthermore, this work does not require additional preprocessing and extraction of features, which is common in the existing methods. This study reached the sensitivity, specificity, and accuracy of 100% in 8 out of 9 scenarios. It is also robust to the measurement noise of level as much as 0 dB. Compared to state-of-the-art algorithms and other common methods, our method outperformed them in terms of sensitivity, specificity, and accuracy. Moreover, it includes the most comprehensive scenarios for epileptic seizure detection, including different combinations of 2 to 5 class scenarios. The proposed automatic identification of epileptic seizures method can reduce the burden on medical professionals in analyzing large data through visual inspection as well as in deprived societies suffering from a shortage of functional magnetic resonance imaging (fMRI) equipment and specialized physician.

INDEX TERMS EEG, epilepsy, seizure, sparse representation-based classification, dictionary learning.

I. INTRODUCTION

As reported by world health organization, about 50 million worldwide are suffering from epilepsy [1]. Epilepsy, as the second most common brain disorder after stroke, is characterized by an unexpected seizure, where, nerve cells generate abnormal electrical activities, which leads to loss of consciousness in a limited period of time [2]. Proper diagnosis of epileptic seizure is essential to control and reduce the risk of epileptic attacks [3]. Currently, the diagnosis of epilepsy is based on neurological examination and auxiliary tests such as neuroimaging and Electroencephalography. EEG signals can reflect epileptic abnormalities between inter-ictal (between seizures) and ictal (during seizures) stages. Typically, neurons are in contact with each other by means of electrical potentials that follow a normal pattern in healthy human brain activity. While an abnormal electrical activity occurs in the brain's neural network during epilepsy, this incremental electrical activity can spread out through the entire cortex. A neurologist traditionally inspects the epileptic malformations. The interpretation of EEG signals using an intuitive evaluation is a time-consuming and tedious task, and the obtained results may vary and are limited according to the level of knowledge and expertise of the related physician.

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The use of anti-epileptic drugs have some restrictions and in 20-30% of patients is unable to control the seizure [3]. However, it is reported that using anti-epileptic drugs within pre-ictal stage might be more effective, which prevents the occurrence of ictal stage and the possible physical damages caused by individual unconsciousness [3], [4]. Therefore, designing an automated computer diagnostic system seems to be essential to detect epileptic states from EEG signals based on machine learning techniques. In addition to helping the expert diagnose the epileptic stages, it will have the ability to continuously monitor the high-risk patients, which alerts the seizure before its occurrence and inform the patient to take the drug. There are several stages of an epileptic seizure (brain activity of an individual with epilepsy), which play a major role in anticipating these seizures. Previous studies show that the seizure process is divided into four stages, including pre-ictal, inter-ictal (pre-seizure disturbances), ictal (during a seizure), and postictal. Evidence suggests that seizures come from a recognizable brain state called pre-ictal, which can be considered as a clue to predict the upcoming stages (ictal) [4]–[6].

In the following, the recent studies on the automatic identification of epileptic seizures are reviewed. Tzallas *et al.* [7] calculated the power spectrum density of the EEG signal segment using a variety of time-frequency distributions and used PSD as a discriminative feature to classify epileptic seizure stages. Adeli *et al.* [8] reported a classification algorithm using wavelet transformation and nonlinear dynamics-based features such as the largest Lyapunov exponent and correlation dimension. Oweis *et al.* [9] extracted frequency features from the Hilbert-Huang transform. They also used the t-test to verify the importance of the features. The accuracy and specificity of their algorithm for classification of 2 epileptic and normal states were reported 94% and 96%, respectively. Bajaj *et al.* [10] used the empirical mode decomposition (EMD) to compute modulation bandwidth features and then utilized least squares-support vector machine (LS-SVM) for classifications. They also used the statistical test of Kruskal-Wallis to verify the features. The sensitivity, accuracy and specificity of their algorithm to classify 2 epileptic and normal states were reported 100%, 99% and 99% respectively. Alam *et al.* [11] used EMD and artificial neural networks (ANN) for the identification of epilepsy. Both the above methods are affected by mode-mixing problems due to the use of EMD, meaning that EMD may result in varying oscillations in the same mode or similar oscillations in different modes. Peker *et al.* [12] extracted five statistical features using dual-tree complex wavelet transform and then applied complex-valued neural network transformations to classify epileptic seizure states in 4 different scenarios. They also used a 10-fold cross validation to evaluate their algorithm. Wang *et al.* [13] introduced an autoregressive multivariate, partially directed coherence and SVM classification for the automatic seizure detection. Samiee *et al.* [14] proposed a rationally discreet short-time Fourier transform and statistical features for the classification of epileptic seizures. Das *et al.* [15] employed normal inverse Gaussian parameters in the wavelet domain into their seizure classification scheme. Guler *et al.* [16] proposed a seizure detection scheme using wavelet coefficients and a multi-class support vector machine based on the Lyapunov exponents. Guo *et al.* [17] presented a seizure detection model using the line length features of EEG wavelet sub-bands, followed by an artificial neural network for classification. Swami *et al.* [18] have extracted features such as energy, Shannon entropy, and few other statistical features from EEG sub-bands and feed them to a general neural regression network classifier. Hassan *et al.* [19] presented an automatic diagnostic design for various epileptic seizures based on the tunable-Q wavelet transformation and bootstrap classification leading to an accuracy of 99%. Sharma *et al.* [20] used flexible analytical time-frequency wavelet transformation and calculated fractal dimensions to discriminate various epileptic states. They have reported an accuracy of 99% for their study based on LS-SVM classifier. Acharya *et al.* [21] proposed conventional neural networks (CNN) for automatic identification of pre-ictal, inter-ictal, and normal states from EEG signal. The proposed CNN architecture includes 10 convolution and 3 fully connected layers, which lead to accuracy and sensitivity of 88% and 95%, respectively.

The main challenge in the automatic identification of epileptic seizures is choosing the distinguishing features in order to discriminate between different stages (including ictal, pre-ictal and etc.). However, in most of the previous works, at first, several time, frequency, time-frequency, and statistical features are extracted, then, the best discriminative features are selected either manually or using conventional feature selection methods [22], [23], which is a time-consuming procedure demanding high computational complexity due to high dimensions and are usually not robust and are computationally intensive [24], [25]. Furthermore, the best features in one case/subject may not be considered as optimum for another one. Therefore, using a generalized method that learns the proper features corresponding to each case/subject is essential. In this respect, methods such as Deep Neural Network (DNN) and Sparse Representation-based Classification (SRC) can provide an end-to-end model without the need for basic knowledge. This will remain as the main advantage of this paper. At first, a sparsifying transform is introduced for the EEG signal of each designated state of epileptic seizure. Then, the proposed online dictionary learning is used to obtain the sparsest representation for each of the states, and SRC is applied in order to identify different classes. The proposed approach can be considered as an end-to-end classifier, in which there is no need to a feature selection/extraction procedure, and the discriminative features of each class will be automatically learned during dictionary learning. In dictionary learning, there are two parameters that need to be optimized, namely, the atoms of the dictionary and the sparse coefficients that relate the atoms of the dictionary to the training data set. Since the dictionary learning problem is NP-hard, dictionary learning algorithms use alternating methods to optimize the parameters. In the first step, called sparse coding, the sparse coefficients are calculated by considering a pre-defined dictionary. The most conventional algorithms used as the first step are Matching Pursuit (MP), OMP [26], [27]. In the second step, the sparse coefficients that are calculated in the previous step are used to update the atoms of the dictionary. These two steps are repeated until the dictionary learning algorithm converges. Most of the attention in the dictionary learning problem is to improve the algorithms used in the second step. Some of the important algorithms that are used in this step are: Method of Optimal Directions (MOD) [28], Recursive Least Squares (RLS) dictionary learning [29], Online Dictionary Learning (ODL) for sparse representation [30] and K-Singular Value Decomposition (K-SVD) method [31]. Methods of dictionary updating are categorized into two ways: batch learning methods and sequential learning methods. In batch learning, the entire training data will be used at once to obtain the dictionary atoms. This approach also has a high computational burden, although the computational burden is comparatively lower in the sequential methods in which the training data is used in a sequential way. In online dictionary learning, which is a sort of sequential learning, its atoms are updated recursively as the new training data, beginning from an initial guess for the dictionary [30], [31].

In this paper, we have also focused on various scenarios for the occurrence of epileptic seizures considered in the related literature (and also the existing datasets) and evaluated the proposed algorithm in 9 most complex scenarios to identify the specific states related to the epileptic seizure. We also presented a proposed algorithm for learning the dictionary for each class. The results very promising, such that in 8 out of 9 scenarios, the classification accuracy was 100% while in the remaining one, it was as much as 95%.

Finally, unbalanced class data is another challenging issue in the previous work, where, the authors used data augmentation methods to make the data from different classes balanced, or some classifiers which are not sensitive to unbalanced class data. In contrast, the our work for dictionary learning is almost insensitive to the unbalanced class population.

The remaining of the paper is organized as follows: The used database and the related mathematical background of SRC are given in Section 2. The theory of the proposed algorithm is discussed in Section 3. The simulation results and comparison of the our study with the state-of-the-art are given in Section 4, followed by the conclusion remarks in Section 5.

II. MATERIALS AND METHODS

In this section, we first introduce the EEG database from the University of Bonn. Then, the mathematical background of the SRC theory will be provided.

A. EEG DATABASE

In this paper, we have used the EEG database created by Andrzezak *et al.* [6] at the University of Bonn. This database

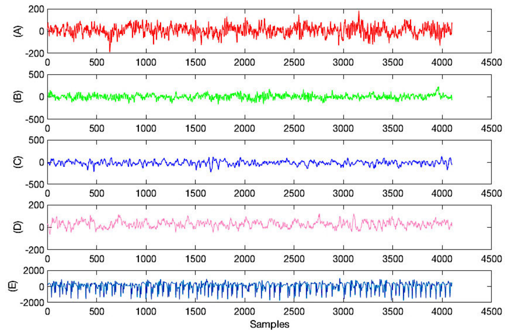

FIGURE 1. Sample EEG epochs belonging to the subsets; A, B, C, D, and E.

is widely used in seizure detection techniques which are publicly available. It consists of 500 single-channel EEG signal epochs in 5 subsets (A, B, C, D, and E) from both normal and individuals suffering from seizure (100 epochs from each subset). Sample EEG epochs belonging to the subsets; A, B, C, D, and E are shown in Fig. 1. Subsets A and B contain EEG data, recorded in a relaxed and awake state from five healthy subjects with open eyes (subset A) and closed eyes (subset B). Subsets C, D, and E were taken from the EEG archive of presurgical diagnosis. Subsets C and D were recorded in five patients who had complete seizure control after epileptic focus resection. The EEG signals in subset C were recorded from the formation of the opposite brain hemisphere (inter-ictal), while the signals in D were recorded from the hippocampal formation identified as an epileptogenic area. Also, signals in two sets have been measured in seizure-free intervals in the epileptogenic zone (D) and from the hippocampal formation of the opposite hemisphere of the brain (C). While subsets C and D contained only activity measured during seizure-free intervals, subset (E) only contained seizure activity. Here for subset (E) segments were selected from all recording sites exhibiting ictal activity. In addition, surface electrodes have been used to record EEG signals for subsets A and B and the implant electrodes used for subsets C, D and E. Apart from the different recording electrodes, the recording parameters were fixed. Fig. 2. shows the areas of the signal recorded for these subsets. All subsets include 100 EEG segments, whereas each segment has a sampling rate of 173.610 Hz for 23.6 seconds (thus containing 4097 samples).

B. SPARSE REPRESENTATION-BASED CLASSIFICATION

In the following, the mathematical background of SRC algorithm is introduced. The main idea in SRC is to obtain a sparsifying transform for each of the classes using training data set and then classify the data from test set based on the residual reconstruction error of the test data using each of the sparsifying transforms [32]. In mathematical terms, a signal $y \in \mathbb{R}^N$ is called k-sparse if at most k out of N samples are nonzero (this is also stated as $y_0 \leq k$, where $\|\|_0$ is the zero norm of vector y). Most of the existing natural signals, including EEG, are sparse or have sparse representation in a

FIGURE 2. Scheme of intracranial electrodes implanted for presurgical evaluation of epilepsy patients. Depth electrodes were implanted symmetrically into the top of the hippocampal formation. Segments of sets C and D were taken from all contacts of the respective depth electrode. Strip electrodes were implanted onto the lateral and basal regions middle and bottom of the neocortex. Segments of set E were taken from contacts of all depicted electrodes [6].

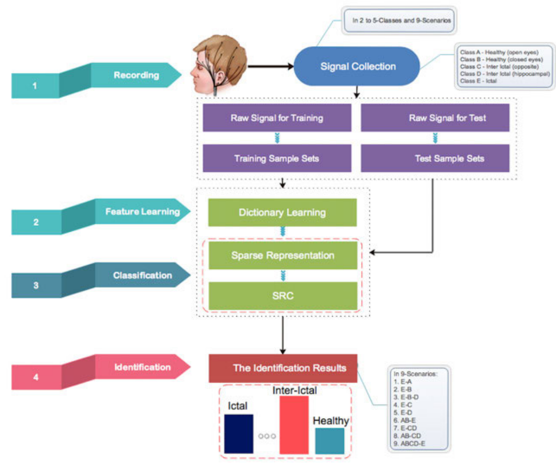

FIGURE 3. The block-diagram of the proposed algorithm.

specific domain (transform). Considering $\phi \in \mathrm{R}^{N\times M}$(which is over-complete if $N < M$) as the sparsifying dictionary, the sparse representation of the data signal vector y can be obtained by solving the linear system of equations $y = \phi x$. Gathering length N data vectors of class i from S EEG recording electrodes in the columns of a single matrix Y^i, the sparse representation model for multi-electrode EEG signal can be obtained as follows:

$$Y^i = \phi^i X^i, \quad i = 1, \ldots, C \tag{1}$$

where C is the total number of classes, $Y^i = \left(y_1^i,\ y_2^i,\ \ldots,\ y_S^i\right) \in \mathrm{R}^{N\times S}$, and $X^i = \left(x_1^i,\ x_2^i,\ \ldots,\ x_S^i\right) \in \mathrm{R}^{M\times S}$ is the corresponding sparse representation. Now, assuming the test data sample Y, the corresponding sparse representation will be obtained by solving the following optimization problem using the dictionaries of each class, to obtain α_i:

$$z_j^i = \min_{\alpha} \alpha_1 \quad \text{s.t. } y_j^i = \phi^i \alpha,\ j = 1, \ldots, S \text{ and } i = 1, \ldots, C \tag{2}$$

where z_j^i is the sparse representation of the j-th column of the test data matrix, i.e., y_j, using the sparsifying dictionary of class i, ϕ^i. Finally, SRC classifies the data by comparing the residual error of the reconstructed EEG signal using the dictionaries of all classes, i.e.,

$$i^* = \underset{i=1,\ldots,C}{\text{argmin}}\ r_i\left(Y\right) = Y - \phi^i Z_F^i \tag{3}$$

where $Z^i = \left(z_1^i,\ z_2^i,\ \ldots,\ z_S^i\right)$, $\|.\|_F$ is the Frobenius norm and for a matrix like $Y \in \mathrm{R}^{N\times S}$ can be calculated as $\|Y\|_F^2 = \sum\limits_{all\ i,j} y_{ij}^2$ where y_{ij} is the entry in the i-th row and j-th column of Y, and i^* is the estimated label of the test data. In many practical cases, however, the test data are accompanied by some bounded observation/measurement noise, where the optimization problem in (2) can be restated as follows in order to account for the noise component:

$$z_j^i = \min_{\alpha} \alpha_1 \quad \text{s.t. } y_j^i - \phi^i \alpha_2 \le \varepsilon, \quad j = 1, \ldots, S \text{ and } i = 1, \ldots, C \tag{4}$$

ε is accounted for the observation noise. For example, if the noise of the observations is zero, the ε will be zero, otherwise, its value is equal to a positive and small number that corresponds to the energy of the noise [32].

Algorithm 1 Sparse Representation Based Classification (SRC)

1. Input: the matrix of training samples $Y^i \in \mathrm{R}^{N\times S}$, a test sample $y \in \mathrm{R}^N$ (collect EEG signals for different states, $i(i = 1,\ 2,\ \ldots, \mathrm{C})$ and divide the signals into two parts for training and testing)
2. Learn the dictionaries $\phi^i(\phi^1$ for $i = 1, \phi^2$ for $i = 2, \ldots, \phi^C$ for $i = C)$ using dictionary learning algorithm.
3. Learn the sparse representations $X^i(i = 1,\ 2,\ \ldots, \mathrm{C})$ by expanding a test sample y on all the dictionaries $(\phi^1, \phi^2, \ldots, \phi^C)$, using OMP.
4. Calculate errors $r_i(i = 1,\ 2,\ \ldots, \mathrm{C})$ defined in Eq. (3).
5. Output: identify (y) using compute i^* defined in Eq. (3). Finding the minimum error, the sample y can be classified into the corresponding state.

III. THE PROPOSED METHOD VIA DICTIONARY LEARNING AND SPARSE REPRESENTATION-BASED CLASSIFICATION

In this section, the suggested method to automatically classification of epileptic seizure states is described. The block diagram of our work can be found in Fig. 3.

In the first phase, the recorded signals are divided into two subsets of test and training data (data collection). In the second phase, the dictionary matrices are updated for the different classes using the training data (dictionary learning). The sparse representation of the test data is obtained in the third stage using the dictionary matrices from the dictionary learning phase and then, they are reconstructed (reconstruction phase). Finally, in the fourth phase, the automatic identification of epileptic seizures is performed based on the difference between the initial (original) and the reconstructed signals from the third stage (classification phase). In the upcoming subsections, at first, online dictionary learning algorithm is discussed, followed by the introduction of the proposed classification procedure and its parameters.

A. THE PROPOSED DICTIONARY LEARNING

In general, the dictionary is referred to a set of atoms (columns of the dictionary matrix), which can be used to represent underlying data as a linear combination of its atoms. Dictionaries which are used to obtain sparse representation for the signals are called sparsifying dictionaries and divided into two categories of deterministic and training-based dictionaries. Deterministic sparsifying dictionaries are not dependent on the underlying signal, like FFT and DCT bases matrices, while the entries of the training-based sparsifying dictionaries are completely dependent on the signal to be represented. Training-based dictionaries are signal-specific and can obtain the sparsest representation of a specific signal. Dictionary learning algorithms use training data in two manners: batch learning methods and sequential learning methods. In batch learning, the whole training data is used at once in order to obtain the atoms of the sparsifying dictionary. This method often has high computational burden, while the sequential methods in which the training data is utilized in a sequential manner have relatively lower computational burden. In online dictionary learning (a kind of sequential learning), starting from an initial solution/guess for the dictionary, its atoms are updated in a recursive manner as the new training data becomes available. In this paper, a new online dictionary learning algorithm, namely, correlation-based weighted recursive least square update (CBWRLSU), is proposed to update the atoms of the dictionary one by one based on their correlation with the new training data. This method has two major advantages: First, it significantly reduces the computational burden of heavy matrix-inversion by reducing the dimension of the matrix, which should be inverted. Second, it prevents the updating of the unnecessary atom. Algorithm 2 shows the summary of CBWRLSU dictionary learning [33].

In this work, instead of the forgetting factor, a new data correlation with the previous data is used and the data correlated with the new data is used to update the atoms of the dictionary as well as the new data from the correction coefficient given in [33].

B. SRC USING PROPOSED CBWRLSU DICTIONARY LEARNING

First of all, for the collected signals of epileptic seizure states, the over-complete learned dictionary from training samples for the state $i (i = 1, 2, \ldots, C)$ using CBWRLSU algorithm is denoted as ϕ_i. Then, the sparse representation for a test data y (of unknown label) will be obtained using all of the C learned dictionaries, leading to their corresponding sparse representations as $X_i, i = 1, 2, \ldots, C$. The reconstruction error for the test data y using the sparsifying dictionary from i-th state, i.e., e_i, can be calculated as:

$$e_i = y - \phi_i X_{i2}^2 \tag{5}$$

Algorithm 2 Proposed CBWRLSU Dictionary Learning Algorithm Method

1. Initialize ϕ and C
2. For $(i = 1 : L)$
3. Get the new training data $\boldsymbol{y_i}$
4. Find $\boldsymbol{X_i}$, sparse representation of $\boldsymbol{y_i}$, using OMP
5. Find $\boldsymbol{\Omega}\left(\boldsymbol{y_i}\right)$, indices of previous signals which use common atoms in their sparse representation with $\boldsymbol{y_i}$
6. Find $\boldsymbol{Y}\left(\boldsymbol{y_i}\right) \in \mathrm{R}^{m \times q_i}$, the set of all previous signals correlated with $\boldsymbol{y_i}$
7. Find $\phi\left(\boldsymbol{y_i}\right)$, the subset of ϕ which deals with $\boldsymbol{Y}\left(\boldsymbol{y_i}\right)$
8. For $(j = 1 : q)$
9. Calculate $\boldsymbol{u_j}\left(\boldsymbol{y_i}\right) = \boldsymbol{C}_{j-1}^{-1}\left(\boldsymbol{y_i}\right)\boldsymbol{X_j}\left(\boldsymbol{y_i}\right)$
10. Calculate $\boldsymbol{e_j}\left(\boldsymbol{y_i}\right) = \boldsymbol{Y_j}\left(\boldsymbol{y_i}\right) - \phi_{j-1}\left(\boldsymbol{y_i}\right)\boldsymbol{X_j}\left(\boldsymbol{y_i}\right)$
11. Calculate $\boldsymbol{\omega}_j\left(y_i\right)$, the correction weight using $\boldsymbol{\omega}_j\left(y_i\right) = \frac{1}{\| e_j(y_i)\|_2^2}$
12. Calculate step size $\boldsymbol{\beta_j}$ using $\boldsymbol{\beta}_j = \frac{\omega_j(y_i)}{1+\omega_j(y_i)X_j^T(y_i)u_j(y_i)}$
13. Update $\phi_j\left(\boldsymbol{y_i}\right)$ using $\phi_{j+1}\left(\boldsymbol{y_i}\right) = \phi_j\left(\boldsymbol{y_i}\right) + \boldsymbol{\beta}_{j+1}\boldsymbol{e}_{j+1}\left(\boldsymbol{y_i}\right)\boldsymbol{u}_{j+1}^T\left(\boldsymbol{y_i}\right)$ and normalize its columns
14. Update $\boldsymbol{C}_j^{-1}\left(\boldsymbol{y_i}\right)$ for next step using $\boldsymbol{C}_{j+1}^{-1}\left(y_i\right) = \boldsymbol{C}_j^{-1}\left(y_i\right) - \boldsymbol{\beta}_{j+1}\boldsymbol{u}_{j+1}\left(y_i\right)\boldsymbol{u}_{j+1}^T\left(\boldsymbol{y_i}\right)$
15. end
16. Replace the updated atoms of $\phi_j\left(\boldsymbol{y_i}\right)$ into the original dictionary ϕ
17. Update sparse coding of $\boldsymbol{y_i}$ using OMP
18. end

Finally, the data will be assigned a label, j^*, based on the solution of the following optimization problem:

$$j^* = \underset{i=1,\ldots,C}{\operatorname{argmin}} e_i \tag{6}$$

This procedure is depicted in Fig. 4. According to Fig.4, the main procedure of the proposed method shall be as follows:

(a) Dictionary learning: supposing there are C predefined patterns of the raw signals, a series of dictionaries ϕ_i $(i = 1, 2, \ldots, C)$ can be learned from the signals in each category via CBWRLSU algorithm, respectively. All the dictionaries are employed to construct a whole dictionary ϕ.

(b) Sparse coding: for a test sample belonging to a certain category, the sparse representation problem can be solved based on the whole dictionary ϕ. Then, the sparse representation vector containing diagnosis information is utilized for further identification and classification.

(c) Classification: all the errors e_i of the test sample can be calculated. Finding the minimum error, the sample can be classified into the corresponding pattern.

The trial and error procedure shall be followed to determine the parameters of this work. This method is described in the

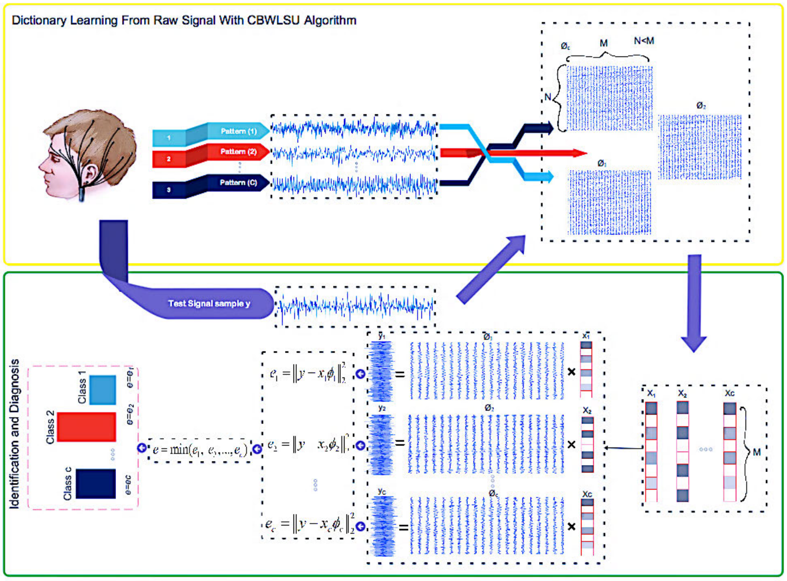

FIGURE 4. Block Diagram for automatic identification of epileptic seizures.

TABLE 1. Nine different classification cases considered in this study and their description.

Case	Class	Account
I	E-A	Seizure and Healthy (eyes-open)
II	E-B	Seizure and Healthy (eyes-closed)
III	E-B-D	Ictal, Healthy (eyes-closed) and Inter-Ictal
IV	E-C	Ictal and Inter-Ictal
V	E-D	Ictal and Inter-Ictal
VI	AB-E	Seizure and Healthy (eyes-open and eyes-closed)
VII	E-CD	Ictal and Inter-Ictal
VIII	AB-CD	Healthy (eyes-open and eyes-closed) and Inter-Ictal
IX	ABCD-E	Healthy (eyes-open and eyes-closed) with Inter-Ictal and Ictal

results section step by step. Since the length of each segment is considered to be equal to the length of the sample data (4097 samples), the dimensions of the sparsifying dictionary are set to 4097×6000. In the training and testing processes, 90% of the data is randomly used for training and the remaining 10% for testing and 10-fold cross-validation is used to evaluate the classifier. The sparsity parameter k is empirically set to 10 for both learning and classification procedures.

IV. SIMULATION RESULTS

The simulation results of our study are presented in this section. The simulations are conducted on a PC with 8 GB of RAM and a 1.6 GHz core i5 CPU. In order to assess the classification performance of the proposed algorithm in different scenarios in terms of complexity as well as clinical relevance, nine different scenarios (namely case I to IX in Table. 1) were considered based on different combinations of the five existing EEG subsets (A, B, C, D and E) introduced in Section 2.1. These cases consist of four 2-class, three 3-class, and one 4-class as well as one 5-class problems, constituting a more practical as well as a fair testbed to compare with the existing state-of-the-art. In order to visually asses the reconstruction performance of the proposed algorithm, a random sample is picked from each of the subsets and the original and reconstructed signals are plotted in Fig. 5, which shows that the reconstructed signals are quite consistent with the original ones. In order to gain more insight, the reconstructed signals of 90 samples of each subset (for training dataset) are shown in Fig. 6 at a particular time instance. Furthermore, as a quantitative measure for the reconstruction performance, the normalized reconstruction error ($E = y - \hat{y}/y$), for the segment of the signal in Fig. 6 is computed and plotted in Fig. 7. Accordingly, it can be concluded that the samples could be efficiently encoded as sparse representations using learned atoms. To put it more clearly, we chose one test sample from each subset (A, B, C, D and E) and the sparse representation coefficients of these five test samples based on their corresponding learned dictionaries are given in Fig. 8.

In terms of the computational complexity of the dictionary learning procedure, the runtime of the proposed algorithm for training each dictionary using the corresponding training dataset is roughly 28 minutes. In other words, a total of 140 minutes was spent on training 5 dictionaries (for each subset), while only 6 seconds were spent on classifying the total testing dataset given the trained dictionaries.

In order to evaluate the classification of the suggested study for 9 different predefined cases, the classification performance in terms of accuracy, sensitivity, and specificity is shown in Table. 2. It is evident from Table. 2 that among various clinically important cases, maximum accuracy, sensitivity, and specificity for 8 out of 9 predefined cases is

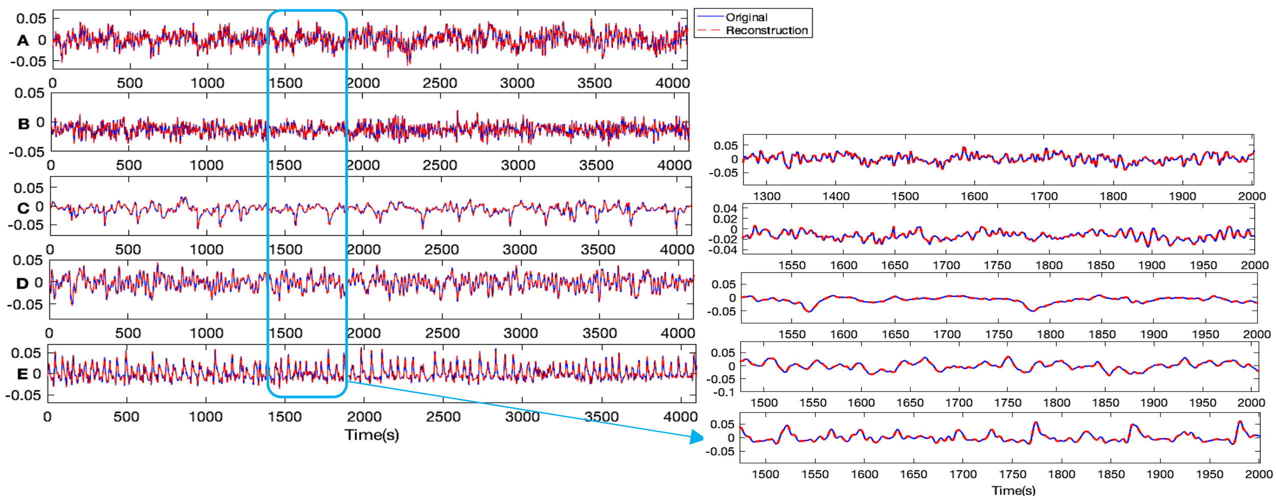

FIGURE 5. Original and reconstructed signals for each subset (A, B, C, D and E) for the sample no 50.

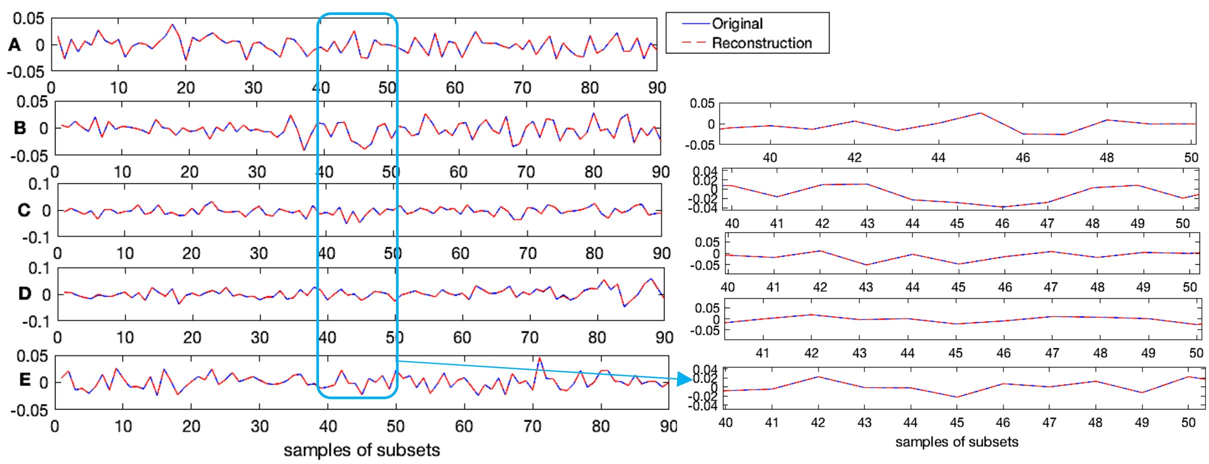

FIGURE 6. 90 samples of the reconstructed signals (for training dataset) at a particular time for each subset.

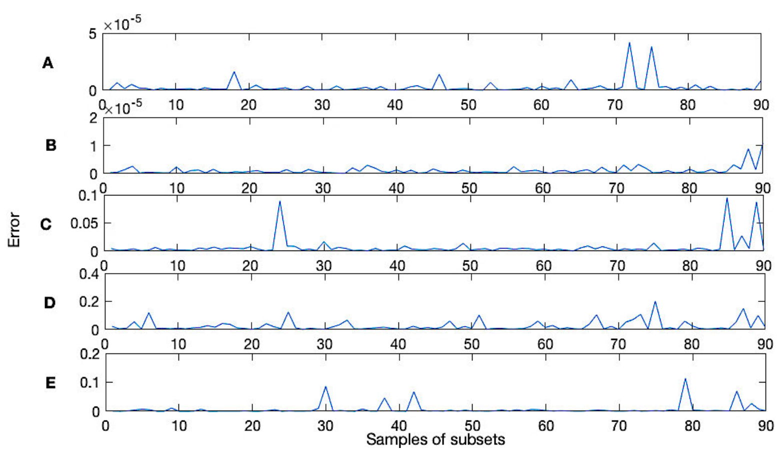

FIGURE 7. Reconstruction error ($E = y - \hat{y}/y$) for the samples of the subsets in Fig. 5.

obtained, which is 100 percent, while the accuracy, sensitivity, and specificity for the remaining VIII case are still very promising.

The different parameters of the proposed method are accurately regulated. The trial and error method was used to adjust these parameters. In this method, in the first step, to determine

TABLE 2. Nine different classification cases considered in this study and their description.

Case	Accuracy (%)	Sensitivity (%)	Specificity (%)
I	100	100	100
II	100	100	100
III	100	100	100
IV	100	100	100
V	100	100	100
VI	100	100	100
VII	100	100	100
VIII	95	95.45	95
IX	100	100	100

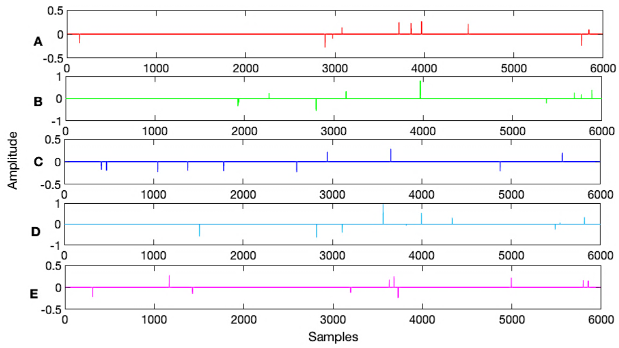

FIGURE 8. 90 samples of the reconstructed signals (for training dataset) at a particular time for each subset.

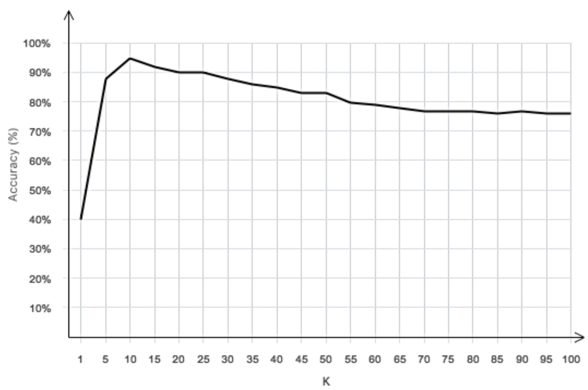

FIGURE 9. Accuracy of the classification obtained for the different sparsity values in the 8th scenario.

TABLE 3. Nine different classification cases considered in this study and their description.

For M=6000			
K	Train time (min)	K	Train time (min)
1	63	50	175
5	91	60	192
10	112	70	209
20	128	80	225
30	142	90	242
40	159	100	257

TABLE 4. The computational efficiency of training time for different dictionary dimensions.

For K=10 M	Train time (min)
100	10
1000	40
3000	79
4097	90
5000	95
6000	112
8000	140
10000	165
12000	186

the optimum value of the sparsity parameter k, different sparsity values are considered for the constant value of M. As shown in Fig. 9, setting the value to 10 for the k parameter will have the highest accuracy for the 8th scenario. According to Table 3, as the value of k increases, training time will also increase. For further examination of Table. 3, it is noted that if the value of k is selected 5 or 1, the training time will be reduced, but in this cases, according to Fig. 9, the accuracy in the range will not be as high as possible. Therefore, according to what has been said, the optimum value for k in terms of accuracy and speed will be 10. Then, in the second step, different values of M are considered for determining the optimum number of columns of the dictionary (M) for the constant value of the k parameter. According to Fig. 10, if the value of M is greater than the value of 4097 (over complete dictionary), the accuracy value will be increased, and when its value is set to 6000, it is observed that the accuracy reaches its maximum value (approximately 95%). After that, as the M value increases, the accuracy remains almost constant. In addition, the smaller the value of M than 4097 (under complete dictionary), the accuracy value is also reduced. For the value of M equal to 4097 (complete dictionary), the accuracy value is approximately 82%. Therefore, it can be stated that the optimum values for the number of columns in the dictionary are $M \geq 6000$. Also, according to Table. 4, by reducing the value of M, the training time of the proposed algorithm is also reduced, but in this situation the accuracy is not acceptable. According to Fig. 10 and Table. 4, the optimal value (both in terms of accuracy and time) the choosing of dictionary dimensions is 6000.

During recent years, several automatic seizure detection methods using EEG signals were proposed. In Table. 5, we compared various studies conducted on the same database to classify different predefined cases using EEG signals. The best results are highlighted in boldface. It is clear from Table. 5 that our method offers the highest accuracy, sensitivity, and specificity for all 9 cases among all the comparative methods. In previous studies, common methods such as WT, EMD, etc. were used to extract the important characteristics and features of the signal, involving some common problems regarding the parameters of the feature selection/extraction procedure such as choosing the type of the mother wavelet,

TABLE 5. The performance of the proposed method compared with the other methods on the Bonn EEG database.

Case	Authors	Accuracy (%)	Sensitivity (%)	Specificity (%)
I	Guo et al. [17]	95.20	98.17	92.12
	Polat et al.* [34]	98.72	99.40	99.31
	Acharya et al. [35]	99	99	99
	Subasi [36]	94.5	95	94
	Tzallas et al.* [7]	**100**	**100**	**100**
	Orhan et al.* [37]	**100**	100	**100**
	Nicolaou et al. [38]	99.50	-	-
	Kaya et al.* [39]	98	99	97
	Peker et al.* [12]	**100**	**100**	**100**
	Samiee et al. [14]	99.80	99.6	99.9
	Swami et al.* [18]	**100**	-	-
	Hassan et al. [19]	**100**	**100**	**100**
	Sharma et al.* [20]	**100**	**100**	**100**
	Proposed Method*	**100**	**100**	**100**
II	Nicolaou et al. [38]	82.88	-	-
	Samiee et al. [14]	99.30	99	99.6
	Swami et al.[18]	98.89	-	-
	Sharma et al.* [20]	**100**	**100**	**100**
	Proposed Method*	**100**	**100**	**100**
III	Guo et al. [17]	93.5	-	-
	Bhattavh et al. [40]	98.6	-	-
	Acharya et al* [21]	87.7	95	90
	Proposed Method*	**100**	**100**	**100**
IV	Nicolaou et al.[38]	88	-	-
	Samiee et al. [14]	98.50	99.3	97.7
	Swami et al.* [18]	98.72	-	-
	Hasan et al. [19]	**100**	**100**	**100**
	Sharma et al.* [20]	99	**100**	98
	Proposed Method*	**100**	**100**	**100**
V	Nicolaou et al. [38]	79.94	-	-
	Kaya et al.* [39]	95.50	96	95
	Siuly et al. [41]	93.60	89.40	97.80
	Kumar et al. [42]	93	94	92
	Alam et al. [11]	**100**	-	-
	Hassan et al. [19]	**100**	**100**	**100**
	Sharma et al.* [20]	98.50	**100**	97
	Proposed Method*	**100**	**100**	**100**
VI	Swami et al. [18]	99	-	-
	Sharma et al. * [20]	**100**	**100**	**100**
	Proposed Method*	**100**	**100**	**100**
VII	Kaya et al.* [39]	97	98	95
	Swami et al.* [18]	95.15	-	-
	Hassan et al. [19]	98.67	98.67	98.67
	Sharma et al.* [20]	98.67	**100**	96
	Proposed Method*	**100**	**100**	**100**
VIII	Sharma et al.* [20]	92.50	90.50	94.50
	Proposed Method*	**95**	**95.45**	**95**
IX	Orhan et al.* [37]	99.60	98.04	**100**
	Guo et al. [17]	97.77	98.61	94.60
	Hassan et al. [19]	99.60	99.49	100
	Sharma et al.* [20]	99.20	**100**	96
	Proposed Method*	**100**	**100**	**100**

(*Using 10-fold cross-validation)

the number of decomposition levels, and etc. One of the most important advantages of our study compared with the other methods is that the feature extraction is automatically done based on dictionary learning, and no feature selection procedure is needed.

To illustrate the performance of the proposed CBWRLS method with various data types as input, the classification accuracy is obtained using the other common methods for 3 different predefined cases (I, III, and VIII). In this regard, time data and several manual features from time data along with BPNN and SVM are selected as the comparative methods [43]–[46]. The Gaussian Radial Basis Function (RBF) is used as the kernel function of the SVM, and the grid search method is used to optimize the kernel parameters. In order to achieve better results from the BPNN model, the number of layers and hyper-parameters are adjusted by different data types. The parameters of the minimum, maximum, skewness, crest factor, variance, root mean square (RMS), mean, and kurtosis are chosen as the manual features of the time domain (time features) [47]. The testing accuracy of the

TABLE 6. The testing accuracy of different methods for identification of epileptic seizures for 3 different predefined cases (I, III and VIII).

Methods	Feature learning from raw data			Manual features		
	Case I	Case III	Case VIII	Case I	Case II	Case VIII
SVM	89.7%	92.2%	81.9%	95.4%	94.1%	91.9%
BPNN	94.3%	94%	88.4%	98.7%	96%	93.2%
P-M (CBWRLSU)	**100%**	**100%**	**95%**	97%	95.3%	92.2%

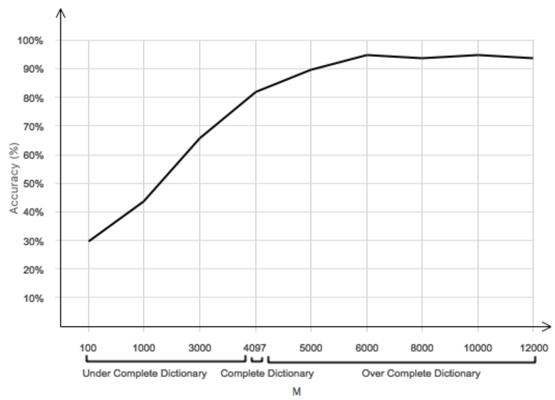

FIGURE 10. Accuracy of the classification obtained for the different dictionary dimensions in the 8th scenario.

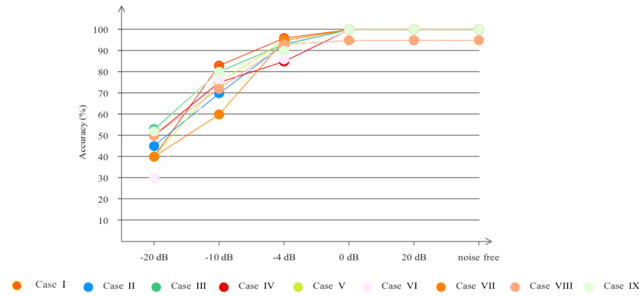

FIGURE 11. Accuracy of the suggested algorithm versus SNR in additive white Gaussian noise scenario.

different methods based on the feature learning from raw data and the manual features are presented in Table 6, where the result of the proposed CBWRLSU method is marked in bold.

Comparing the performance of feature learning and manual features, feature learning from raw time data with the proposed CBWRLS method provides better results than manual features. This result is significantly correlated with the unique Algorithm 2 of the proposed CBWRLS method, which can automatically extract the useful features for classification. While proposed CBWRLS has a better result with feature learning from raw time data, all the tested models, including CBWRLS, BPNN and SVM provide similar results with manual features. This indicates that the CBWRLS cannot achieve further more improvements in the identification of epileptic seizures than traditional methods without the ability of feature learning.

In order to assess the performance of the suggested work against observation noise, the white Gaussian noise of SNR -20 to 20 dB is added as the measurement noise to the EEG signals and the classification accuracy for all 9 cases is reported in Fig. 11. As it is seen, the classification performance of the suggested method is considerably robust to the measurement noise in a wide range of SNR, such that the accuracy is still more than 80% for SNR of -4 to 20 dB.

Due to the high performance of the proposed algorithm classification for automatic detection of various stages of epileptic seizures, In the near future, it is felt that using the proposed method as an intelligent medical assistant in the emergency departments (EDs) can detect non-convulsive status epilepticus (NCSE) cases quickly and automatically. Non-convulsive seizure (NCS) is defined as a cerebral ictal activity with no clear clinical evidence of motor activity [48], [49]. This is the root cause of approximately 5 percent of patients with altered mental status (AMS) presenting to the Emergency Department (ED). Nearly half of these NCS cases are in the form of non-convulsive status epilepticus (NCSE) [50]. The mental shift can be in the form of confusion, lethargy, delirium, anxiety, coma, or even depression or improper behavior. Electroencephalography (EEG) continues to be the gold standard for NCS diagnoses. EEG is however not routinely available in most EDs [51], [52]. The treatment of this time-sensitive neurological emergency is still a challenge for emergency physicians. Therefore, the diagnosis of this time-sensitive neurological emergency remains a challenge for emergency physicians. However, in another study, it is necessary to examine the performance of the proposed algorithm in a comprehensive database of NCSE cases. The use of the proposed method is expected to reduce the mortality rate from NCSE cases.

Despite the contributions, this work has some limitations, as with other previous studies. First, notwithstanding the use of the Bonn database, a clinical validation study based on a bigger dataset is still necessary. Second, the training time of the proposed algorithm is relatively high, which can be solved using graphical processing unit (GPU) systems.

V. CONCLUSION

In this paper, a new method for automatic identification of epileptic seizures is presented using SRC and proposed dictionary learning. In this study, the EEG signals are used to separate 2 to 5 classes in 9 different scenarios using the dataset recorded at the University of Bonn. We achieved 100% accuracy, sensitivity and specificity for all scenarios except C-VIII, which is very promising compared to the state-of-the-art seizure detection approaches. Furthermore, it is shown that the our method is robust to the measurement noise of level as much as 0 dB. Due to fatigue and the need for expert human resources, detection of the various states of the epileptic seizure based on visual examination is unpleasant, time-consuming, and erroneous and also leads to low accuracy in the identification. However, with the expansion of the proposed method, this method can be used in the near future as a medical assistant to automatically detect the various states of the epileptic seizure from EEG signals with an accuracy of more than 95%. Also, the proposed algorithm can also be used to automatically detect the non-convulsive status epilepticus (NCSE), which is a big challenge by physicians to diagnose. Automatic identification of the epileptic seizure not only causes quick diagnosis but also reduces the workload of doctors and is very effective in timely treatment and reduction of patient mortality.

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