Detection of Brain Interictal Epileptiform Discharges from Intracranial EEG by Exploiting their Morphology in the Tensor Structure

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***Abstract*—Detection of interictal epileptiform discharges (IEDs) from EEG signals is the mainstay of diagnosis of epilepsy. The diversity in IED morphologies and their weakness deteriorate the detection performance particularly when the IEDs of different subjects are combined for training. Here, we propose an IED detection system based on tensor factorization in which IEDs with similar morphology are concatenated into the same slice of a tensor. Applying the proposed method to the intracranial EEG 92.9% accuracy has been achieved. This shows that incorporating IED shape diversity into tensor factorization considerably improves the results.**

***Index Terms*—Epileptiform discharges, IED morphology, intracranial EEG, spatial components, tensor decomposition**

I. Introduction

Epileptic seizures occur due to excessive discharges of groups of brain cells in the cerebral cortex or hippocampus. In the diagnosis of epilepsy and localization of seizure onset sources, both the interictal and ictal recordings are extremely informative. Spikes and sharp waves, known as interictal epileptiform discharges (IEDs), elicit between two seizure onsets, detection of which is of great importance in the diagnosis and management of epilepsy. EEG recordings are able to capture the IED signatures [1].

IEDs are consisted of spikes, with the duration of 20-70 ms; sharp waves, with the duration of 70-200 ms; and slow waves, with a duration of longer than 125 ms. Therefore, in terms of their morphology, IEDs can fall into five groups: (1) polyspike complex: A sequence of two or more spikes which may or may not be an epileptiform pattern; (2) sharp-and-slow-wave complex: an epileptiform pattern consisting of a sharp wave followed by a slow wave; (3) spike-and-slow-wave complex: An epileptiform pattern consisting a spike followed by a slow wave; (4) six Hz spike-and-slow-wave: Spike-and-slow-wave complexes occurring generally in brief bursts bilaterally and synchronously at 4–7 Hz, but mostly at 6 Hz; and (5) multiple spike-and-slow-wave complex, An epileptiform pattern consisting of two or more spikes associated with one or more slow waves [2].

Multiway analysis (e.g., tensor decomposition) provides an opportunity to simultaneously analyze multi-aspects of data (e.g., time, space, frequency, segment, subject, and morphology). It has been widely employed for EEG signal processing [3] particulary epilepsy signal analysis [4], [5]. In [5], Stockwell transform was employed to obtain frequency features, and Tucker decomposition (TD) to decompose the tensor into its factors and the core tensor. Then, the core tensor was used as the EEG features for seizure detection. Spyrou *et al.* proposed two IED detection methods based on TD to detect IEDs from intracranial EEG (iEEG) [6] and scalp EEG [7]. To detect epileptic and non-epileptic spikes, Thanh *et al.* [8] constructed a four-way tensor of time, channel, frequency, and epileptic segment and applied nonnegative TD for decomposition. They projected epileptic and non-epileptic spikes onto the temporal, spatial, and spectral factor matrices, and used the projected segments for classification. We have already developed a tensor-based method to incorporate uncertainty in IED labeling into an automatic IED detection system [9].

Incorporating information that has diversity in their shapes into the same slice of a tensor can deteriorate the factors obtained using tensor decomposition. Due to this fact, Thanh *et al.* [8] put only epileptic spikes in the fourth slab of the tensor. However, the epileptic spikes or IEDs have various morphologies and strengths. To the best of our knowledge, there is no study to consider the impact of morphology of IEDs in an automatic IED detection system. Therefore, we propose a model based on tensor factorization to take the effect of IED morphologies into account.

II. Method

Here, a tensor-based IED detection model is proposed. The IEDs may share some spatial and morphological information with each other. Nonetheless, the non-IED segments can be non-epileptic spikes or normal brain activities, and hence there is no common information among them. Therefore, the feature space including only the IED segments can be more reliable and discriminative. Furthermore, since the IED morphologies can be different, we are interested in separating the IEDs with different scores by exploiting their morphological diversities. In this study, the IEDs are given a score based on their morphology and spatial information by an expert epileptol-

ISBN: 978-9-0827-9706-0

ogist. IEDs with similar scores are concatenated into a three-way tensor with the dimensions of time samples, channels, and IED segments of the same scores. Next, all three-way tensors are concatenated into a single four-way tensor with the dimensions of time, channel, IED segment, and morphology (score). The CANDECOMP/PARAFAC decomposition (CPD) algorithm developed by Acar *et al.* [10] is then employed to extract the tensor factors (it should be noted that other tensor factorization methods such as TD or block term decomposition can be used instead). Finally, both IEDs and non-IEDs are projected onto the spatial and morphological components to achieve the most discriminative features. This model is called IED detection based on spatial and morphological component analysis exploiting the IED scores (SMCA-Sc).

Suppose we are given N_1 IED segments with different morphologies (scores) and N_2 non-IED segments. We construct a four-way tensor $\boldsymbol{\mathcal{X}} \in \mathbb{R}^{L\times M\times \widetilde{N}\times S}$, where L and M denote respectively time samples and the number of channels, $\widetilde{N}$ corresponds to the number of IED segments in each group which needs to be equal, and S is the number of morphological groups.

CPD is employed to decompose tensor $\boldsymbol{\mathcal{X}}$ into its factor matrices:

$$\min_{\mathbf{A},\mathbf{B},\mathbf{C},\mathbf{D}} \quad f \equiv \frac{1}{2}\left\|\boldsymbol{\mathcal{X}} - [\![\mathbf{A},\mathbf{B},\mathbf{C},\mathbf{D}]\!]\right\|^2, \tag{1}$$

where $\mathbf{A} \in \mathbb{R}^{L\times R}$ and $\mathbf{B} \in \mathbb{R}^{M\times R}$ correspond respectively to the temporal and spatial factors, and $\mathbf{C} \in \mathbb{R}^{\widetilde{N}\times R}$ and $\mathbf{D} \in \mathbb{R}^{S\times R}$ are respectively the segmental and morphological factors. Note that R is the number of components.

As IEDs originate from temporal lope regions and a large proportion of them are captured by the same electrode for the same subject, the spatial components can provide the most discriminative features. Moreover, morphological components are informative due to capturing the IED waveform information. Therefore, both IED and non-IED segments of the training and test datasets are projected onto the spatial and morphological factors as follow:

$$\mathbf{Y}_n = \mathbf{X}_n\mathbf{B}\mathbf{D}^T \tag{2}$$

where $\mathbf{X}_n \in \mathbb{R}^{L\times M}(n = 1,\ldots,N_1 + N_2)$ is an IED or non-IED segment from the training or test datasets and $\mathbf{Y}_n \in \mathbb{R}^{L\times S}(n = 1,\ldots,N_1 + N_2)$ is the same segment after projection. Now, features of $\mathbf{Y}_n$ are extracted and used for classification. Here, we extract time-frequency (TF) features using the spectrogram method. The schematic of proposed SMCA-Sc method is illustrated in Fig. 1.

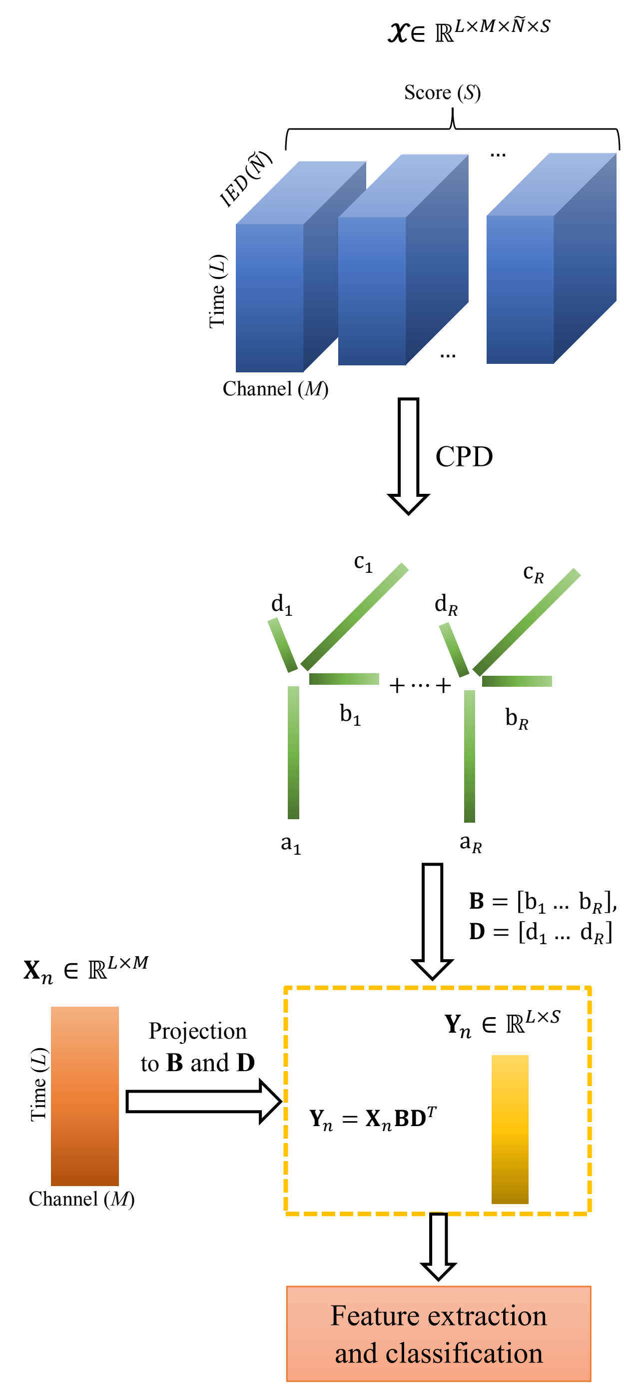

Fig. 1. The schematic of proposed SMCA-Sc model. $\boldsymbol{\mathcal{X}}$ includes the IED segments which are concatenated in four-way tensors according to their scores given by an expert based on the IED morphologies. CPD is applied to $\boldsymbol{\mathcal{X}}$ to decompose it to temporal, spatial, segmental, and morphological factors. $\mathbf{X}_n(n = 1,\ldots,N_1 + N_2)$ is an IED or non-IED segment from the training or test data. $\mathbf{Y}_n$ represents the same segment after projection onto the spatial $\mathbf{B}$ and morphological $\mathbf{D}$ components.

III. Experiments

A. Dataset

The scalp EEG and iEEG signals of 18 epileptic subjects were simultaneously recorded at King's College Hospital London. Here, we analyzed 20-minute iEEG recordings, which were recorded at a sampling rate of 200 Hz by using 12 intracranial multicontact foramen ovale electrodes consisting of a couple of 6 electrode bundles. A bandpass filter with cut-off frequencies of 0.3 and 70 Hz was employed during recording [11].

TABLE I
THE TOTAL NUMBER OF IED AND NON-IED SEGMENTS FOR EACH SUBJECT. THE SAME NUMBER OF IED AND NON-IED SEGMENTS WERE CHOSEN FOR EACH SUBJECT.

Subject	No. of segments	Subject	No. of segments
S1	38	S10	622
S2	524	S11	692
S3	302	S12	344
S4	108	S13	26
S5	158	S14	20
S6	648	S15	692
S7	250	S16	22
S8	552	S17	178
S9	38	S18	338

B. IED Scoring and Preprocessing

An expert epileptologist identified the IEDs and gave a score between 1 to 5 for each IED based on their morphology and spatial distribution of the observed waveforms. The IEDs scored the same look approximately similar in morphology.

The iEEG recordings are filtered using a Butterworth filter of order six and cut-off frequencies of 4 and 70 Hz. The highpass frequency of 4 Hz has been selected to eliminate eye blink artifacts. In addition, a 50 Hz notch filter was employed to remove the power line interference.

The iEEG signals were segmented into IED and non-IED segments before classification. The length of IEDs was selected to be 480 ms (96 time samples) – 160 ms before and 320 ms after the positions of peaks manually marked as IED by an expert. Non-IEDs with the same length as IEDs were selected from time segments where there was no sign of IEDs. Note that, non-IED segments included non-epileptic spikes and sharp waves, biological and non-biological artifacts, and normal brain activities. The number of non-IEDs was randomly selected to be the same as the number of IEDs to have a balance classification problem. The number of segments are illustrated in Table I.

C. IED Detection Based on SMCA-Sc

A three-way tensor is constructed for IEDs with the same score. In other words, we construct five three-way tensors each with a different score. The number of IEDs in each three-way tensor is set to the lowest number of IEDs scored 1, 2, 3, 4, or 5. Then, all five three-way tensors are concatenated into a single four-way tensor, $\boldsymbol{\mathcal{X}} \in \mathbb{R}^{96\times 12\times \widetilde{N}\times 5}$, where 96 is time samples, 12 is the number of channels, $\widetilde{N}$ denotes the number of IED segments, and 5 corresponds to the number of scores. CPD is employed to decompose the tensor into temporal, spatial, segmental, and morphological factors. In CPD, the number of components, R, has to be less than or equal to the lowest number of observations in tensor's modes. Thus, it cannot be bigger than 5 in our study, and it was set to the maximum value of 5. As a result, the factor are $\mathbf{A} \in \mathbb{R}^{96\times 5}$, $\mathbf{B} \in \mathbb{R}^{12\times 5}$, $\mathbf{C} \in \mathbb{R}^{\widetilde{N}\times 5}$, and $\mathbf{D} \in \mathbb{R}^{5\times 5}$. After projecting IED and non-IED segments ($\mathbf{X}_n$) onto the spatial and morphological components using 2, the projected IEDs and non-IEDs ($\mathbf{Y}_n$) have the dimensions of 96×5.

The TF features of the projected segments are exploited using the spectrogram. A Hanning window of the length of 80 ms (16 samples) and overlapping of 50% slid over each channel of the projected segments (five channels) to obtain time-frequency features (totaly11 windows). The squared magnitudes of short-time Fourier transform obtained using the spectrogram are utilized as classification features. The number of discrete Fourier transform points has been set to 16 (the same as the number of time samples in a window) resulting in 9 frequency features. Finally, $11 \times 9 \times 5$ features (495) were obtained from each IED or non-IED segment, where 11 is the number of time slabs, 9 is the number of frequency slabs, and 5 is the number of morphological groups (the number of channels of the projected segments).

D. Compared Methods

To show the effect of incorporating the IED morphologies in an IED detection system, the IEDs were randomly concatenated into a single four-way tensor with the same dimension as it is constructed for SMCA-Sc. Decomposition, projection, feature extraction, and feature selection methods were performed in the same manner as it was performed in the proposed method. This model is called spatial and morphological component analysis based on non-scored IEDs (SMCA-nS).

We also compared our proposed SMCA-Sc method with a method namely spatial component analysis (SCA) in which all IEDs are concatenated into a three-way tensor [9]. We already proposed SCA to detect IEDs from scalp IEDs. In SCA, a three-way tensor of time, channel, and IED segment is constructed. CPD is employed to decompose the tensor into temporal, spatial, and segmental factors. For a fair comparison, five components ($R = 5$) giving the best performance are extracted like SMCA-Sc or SMCA-nS. Finally, both IEDs and non-IEDs are projected onto the spatial components. After projection, the same feature extraction and selection are applied to extract the significant features.

In [12], the authors proposed a binary convolutional neural network (CNN Bin) and a multiclass CNN (CNN Multi) to detect IEDs in which the same data was utilized. In CNN Bin, the IEDs and non-IEDs were detected in a binary classification approach. In CNN Multi, the authors detected IEDs based on their scores. In addition, the results of wavelet features (WF) and TF features (TFF) extracted from the raw iEEG in the same manner done here were reported in [12]. Here, we compare our proposed SMCA-Sc method with CNN Bin, CNN Muti, WF, and TFF.

We also made a comparison with a TD-based method in which the authors used the same dataset [6]. In the TD method, TF features were extracted using the spectrogram method. Then, a three-tensor – with the dimension of channel, time, and frequency – was constructed and decomposed using TD. Finally, IED and non-IED segments were projected onto the spatial components. Here, we compare our developed SMCA-Sc method with TD developed in [6].

E. Feature Selection and Classification

Fisher score method was employed to select the most significant features, which is defined as:

$$f_i = \frac{\sum_{c=1}^{c=C} n_c(\mu_{ic} - \mu_i)^2}{\sum_{c=1}^{c=C} n_c \sigma_{ic}^2}, \tag{3}$$

where μ_{ic} and σ_{ic} denote respectively the mean and standard deviation of the i-th feature in the c-th class, n_c is the number of instances in the c-th class, and μ_i is the mean of the i-th feature.

Decision tree ensembles (DTE) with bagging technique, naïve Bayes (NB), k-nearest neighbors (KNN) with $k = 3$, and KNN with $k = 5$ were employed and compared for classification.

F. Evaluation and Cross Validation

Leave-one-subject-out cross validation was employed to validate the models. The IEDs and non-IEDs of a subject used as the test data, others were utilized for training the classifiers.

For evaluation of the methods, accuracy (ACC), sensitivity (SEN), specificity (SPEC), F1 score (F1-S), and area under the receiver operating characteristics (AUROC) were obtained as follows:

$$\text{ACC} = \frac{TP + TN}{TP + FP + TN + FN} \times 100\%, \tag{4}$$

$$\text{SEN} = \frac{TP}{TP + FN} \times 100\%, \tag{5}$$

$$\text{SPEC} = \frac{TN}{TN + FP} \times 100\%, \tag{6}$$

$$\text{F1-S} = \frac{2TP}{2TP + FP + FN}, \tag{7}$$

where TP denotes the number of IED samples recognized correctly in the IED class, TN is the number of non-IED samples classified accurately as non-IED samples, FP represents the number of non-IED samples categorized wrongly as IED samples, and FN indicates the number of IED samples detected incorrectly in the non-IED class. Accuracy shows the percentage of detection of IED and non-IED samples, and sensitivity and specificity respectively indicate the performance of classifiers in correctly detecting the IED and non-IED samples.

IV. Results

First, we compare our proposed SMCA-Sc method with SMCA-nS and SCA, all of which are based on spatial components as well as CPD. The obtained results are shown in Table II. KNN models are based on the first 10 features and NB is based on the first 30 features obtained using the Fisher score. In DTE, the first 80 features were utilized in SMCA-nS and SMCA-Sc methods, and the first 100 features were employed for the SCA method. These numbers of features gave the best performances in their models.

In both KNNs, SMCA-Sc outperformed the compared methods. In KNN with $k = 3$, SMCA-Sc provided 86.7% accuracy which was approximately 2% higher than SMCA-nS and SCA accuracy values. In KNN with $k = 5$, SMCA-Sc presented the best accuracy of 87% which was respectively 1.6% and 4.2% higher than those of SCA and SMCA-nS. In terms of SEN and SPEC, SMCA-Sc outperformed SMCA-nS and SCA as well in both KNNs. SMCA-Sc presented 0.84 F1-S, which was 0.02 to 0.06 more than the compared methods' F1-S values.

TABLE II
The performance of classifiers with results averaged over all subjects. The classifiers were trained and tested using leave-one-subject-out cross validation. ACC, SEN, and SPEC are presented in percent %.

Classifiers	Method	ACC	SEN	SPEC	F1-S	AUC
KNN(k=3)	SCA	84.8	77.4	92.2	0.81	0.91
	SMCA-nS	84.6	74.5	94.8	0.81	0.91
	SMCA-Sc	**86.7**	**78**	**95.4**	**0.84**	**0.93**
KNN(k=5)	SCA	85.4	77.8	93	0.82	0.93
	SMCA-nS	82.8	72.5	93.1	0.78	0.92
	SMCA-Sc	**87**	**77.7**	**96.2**	**0.84**	**0.94**
NB	SCA	84.4	71	97.8	0.79	0.88
	SMCA-nS	82.8	68	97.6	0.75	0.86
	SMCA-Sc	**86.4**	**74.8**	**98**	**0.83**	**0.9**
DTE	SCA	92.6	**89.7**	95.6	**0.92**	0.99
	SMCA-nS	91.9	89.2	94.6	0.91	0.99
	SMCA-Sc	**92.9**	**89.7**	**96.1**	**0.92**	0.99

TABLE III
Comparing the proposed SMCA-Sc model with WF, TFF, TD, CNN Bin, and CNN Multi proposed in [6] and [12]. ACC, SEN, and SPEC are presented in percent %.

Method	ACC	SEN	SPEC	F1-S	AUC
WF	72.3	70	72	0.73	0.73
TFF	85.6	78	72	0.76	0.85
TD	86	-	-	-	-
CNN Bin	85.9	90	87	0.88	0.88
CNN Multi	89	**94**	81	0.88	0.9
SMCA-Sc	**92.9**	89	**96**	**0.92**	**0.99**

Using NB classifier, SMCA-Sc method detected the IEDs and non-IEDs with 86.4% accuracy, while SCA and SMCA-nS respectively presented 84.4% and 82.8% accuracy values. In terms of SEN, SMCA-Sc significantly outperformed the compared method, though all models presented the comparative SPEC values. SMCA-Sc provided the best F1-S and AUC as well.

In DTE, SMCA-Sc provided the best ACC of 92.9% and SPEC of 96.1% followed by SCA with a small difference. In terms of SEN and F1-S, SMCA-Sc and SCA achieved the comparative values and all three methods obtained 0.99 AUC.

Overall, all methods in all four types of classifiers resulted in higher SPEC than SEN. SPEC values were higher than 90% in all models, while SEN values were less than 80% in all methods when KNNs and NB classifications were employed. In DTE, there was an appropriate trade-off between SEN and SPEC in all methods.

Furthermore, we made a comparison with TD developed in [6] and with WF, TFF, CNN Bin, and CNN Multi proposed in [12]. The results are illustrated in Table III. The performance of SMCA-Sc using the DTE classifier leads to the best performance.

Our proposed SMCA-Sc model significantly outperformed the compared methods by providing 92.9% accuracy. Among the compared methods, CNN Multi presented the highest accuracy of 89% which was approximately 4% less than that of SMCA-Sc. Although CNN Multi detected IEDs with the highest SEN of 94%, SMCA-Sc leads to the best values of SPEC, 96%, F1-S, 0.92, and AUC, 0.99.

V. Conclusion

Detecting IEDs plays a pivotal role in the diagnosis of epilepsy. Here, we proposed a new method based on spatial and morphological components for IED detection. The proposed SMCA-Sc method was compared with 1) SMCA-nS, 2) SCA, 3) WF, 4)TFF, 5) TD, 6) CNN Bin, and 7) CNN Multi. SMCA-Sc outperformed all compared methods and detected IEDs with 92.9% accuracy. The only difference between SMCA-Sc and SMCA-nS is that the IEDs are randomly concatenated into four-way tensor data, not based on their scores, in SMCA-nS. In addition, the difference between SMCA-Sc and SCA is that all IEDs are concatenated into a three-way segment without considering their scores. The findings show that taking the IED morphologies into account in an IED detection system can boost the model performance.

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