EPILEPTIC STATE SEGMENTATION WITH TEMPORAL-CONSTRAINED CLUSTERING

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ABSTRACT

Automatic seizure identification plays an important role in epilepsy evaluation. Most existing methods regard seizure identification as a classification problem and rely on labelled training set. However, labelling seizure onset is very expensive and seizure data for each individual is especially limited, classifier-based methods are usually impractical in use. Clustering methods could learn useful information from unlabelled data, while they may lead to unstable results given epileptic signals with high noises. In this paper, we propose to use Gaussian temporal-constrained k-medoids method for seizure state segmentation. Using temporal information, the noises could be effectively suppressed and robust clustering performance is achieved. Besides, a new criterion called signed total variation (STV) which describes temporal integrity and consistency is proposed for temporal-constrained clustering evaluation. Experimental results show that, compared with the existing methods, the k-medoids method with Gaussian temporal constraint achieves the best results on both F1-score and STV.

Index Terms— Clustering, temporal constraint, epilepsy, sequence segmentation

1. INTRODUCTION

Epilepsy is a serious brain disorder which affects about 50 million people worldwide [1, 2]. Intracranial Electroencephalography (iEEG) [3] is one of the most useful techniques to diagnose epilepsy, to predict seizure [4], and to localize the seizure onset zone. Seizure state identification is an important procedure in epilepsy evaluation. Commonly, this work is performed by visually inspection of clinical doctors, which could be highly tedious and time-consuming. Therefore, reliable automatic seizure detection is of high importance, which would facilitate seizure diagnosis and has great potential in clinical applications.

Although efforts have been made, robust seizure identification is still challenging. Most existing methods regard seizure identification as a classification problem and rely on labeled data [5], making them impractical in clinical applications. Labeling epileptic signals could be very expensive and seizure data for each individual is especially limited. Therefore, classifier-based methods could not be well trained with such small training set.

Recently, some methods have been proposed to track epileptic states using unsupervised algorithms [6, 7, 8, 9]. In their methods, brain states were represented by brain connectivities [10], and state segmentations were achieved using clustering approaches. The unsupervised methods do not rely on labelled data so that they were promising for the clinical use. However, the performance is usually unstable because the epileptic networks change continuously. Thus, the temporal information is important to find and distinguish the different states, which was not sufficiently taken into account in most existing clustering methods [7, 8]. In addition, noises in iEEG signals also have a negative impact to the unsupervised approaches.

Since the dynamics of epileptic networks change gradually over time, the networks at different time are not suitable to be considered as the time-independent clustering samples. Moreover, it is difficult to extract effective features representing epileptic states from noisy signals [11] without the help of temporal information. In this case, we consider the following two aspects to add the temporal constraint to clustering method [12, 13]. On one hand, the adjacent samples could be segmented into a state with a higher probability than distant samples. On the other hand, two groups of networks which are clustered together should be divided into two states if they are apart over time.

In this paper, we propose to use Gaussian temporal-constrained k-medoids method for seizure state segmentation. Using temporal information, the noises could be effectively suppressed and robust clustering performance is achieved. Besides, a new criterion called signed total variation (STV) which describes temporal integrity and consistency is proposed for temporal-constrained clustering evaluation. Experimental results show that, compared with the existing methods, the k-medoids method with Gaussian temporal constraint achieves the best results on both F1-score and STV.

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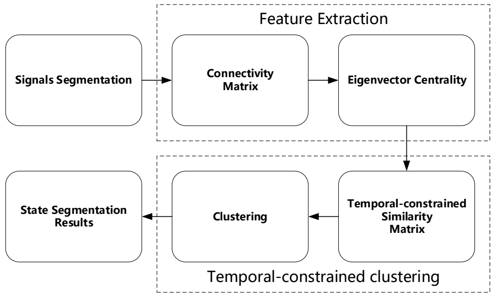

Fig. 1. The framework of our method

2. OUR METHOD

The proposed method is composed of three functional blocks: signal feature extraction over time, similarity matrix computation with temporal constraint, and epileptic states segmentation. Each of functional blocks is described in the following sections and the detailed framework of our method is shown in Figure 1.

2.1. Signal Feature Extraction

It is important to extract effective features from the multi-channel iEEG signals for epileptic seizure analysis. The eigenvector centrality (EVC) [14] is employed as our signal feature extraction method which is computed from connectivity matrix denoted as C. Coherence [15] is a widely used measure to compute the functional connectivity between signals. Coherence is estimated by the spectral density function and the value $C_{i,j}$ between ith and jth channel of signals could be formulated as below:

$$C_{i,j} = \frac{|P_{i,j}|^2}{P_{i,i}P_{j,j}}, \tag{1}$$

where $P_{i,j}$ is the cross-spectral density function and $P_{i,i}$, $P_{j,j}$ are the auto-spectral density function. The calculated values are elements of connectivity matrix C. With these connectivity matrices, the brain networks are built to carry out the analysis of network dynamics. The eigenvector centrality (EVC) is used to measure the importance of vertices in brain networks, which is the foundation of the following methods. The EVC considers not only the number of connections from one vertex to other vertices in brain networks but also the strength of them. The EVC could be formulated as below:

$$C * EVC = \lambda_{max} * EVC, \tag{2}$$

where the EVC is the leading eigenvector centrality corresponding to C and λ_{max} is the maximum eigenvalue of this matrix.

2.2. Similarity Matrix Computation with Temporal Constraint

Given a period of multi-channel signals, the coherence matrices are computed by sliding windows method and we could obtain a sequence of connectivity matrices. A sequence of EVCs denoted as $\{EVC_{t_i}\}, i = 1, 2, ..., N$, computed from connectivity matrices are data samples for analysis. Our goal of epileptic states segmentation is to temporally segment the epileptic brain network dynamics into some consecutive states. Specifically, we want to segment the EVC sequence into some clusters. The EVCs in the same clusters are similar and the EVCs in different clusters have low similarities. But the existing segmentation methods neglect the temporal relationship which is important for signal data and beneficial for segmentation results. The EVCs which are close in time dimension should be more similar comparing to the ones far away. Hence, the temporal constraints between EVCs need to be considered. The temporal sequence index scores are used to compute the similarity between EVCs with a Gaussian constraint or a constant constraint. The similarity S_{t_i,t_j} between EVC_{t_i} and EVC_{t_j} with Gaussian temporal constraint could be formulated as below:

$$S_{t_i,t_j} = d_{t_i,t_j} * exp(-\frac{(t_i - t_j)^2}{2 * \sigma^2}), \tag{3}$$

where the d_{t_i,t_j} denote the classic similarity corresponding to Euclidean distance between EVC_{t_i} and EVC_{t_j}, σ is the decay parameter which controls the decreasing ratio of similarity as the temporal interval increasing. The similarity with constant temporal constraint could be formulated as below:

$$S_{t_i,t_j} = \begin{cases} d_{t_i,t_j} & \text{for } |t_i - t_j| < L, \\ 0 & \text{otherwise.} \end{cases} \tag{4}$$

where the L is a constant. The similarity matrix S of EVCs in a period of time could be constructed in this way.

2.3. Epileptic States Segmentation

With the similarity matrix S, the clustering method is used to segment the EVCs into clusters in which the EVCs are consecutive in time dimension. We suppose that the clusters could reflect different epileptic states. We choose the k-medoids [16] algorithm to do the segmentation part. Unlike the k-means algorithm, the k-medoids algorithm chooses samples existed as centers. Since we could not consider the temporal constraint on the EVCs, and the centers chosen by k-means may not appear in our EVC sequence, we could employ the k-medoids with S which contains temporal constraints. K-medoids algorithm is more robust to noise and outliers compared to k-means.

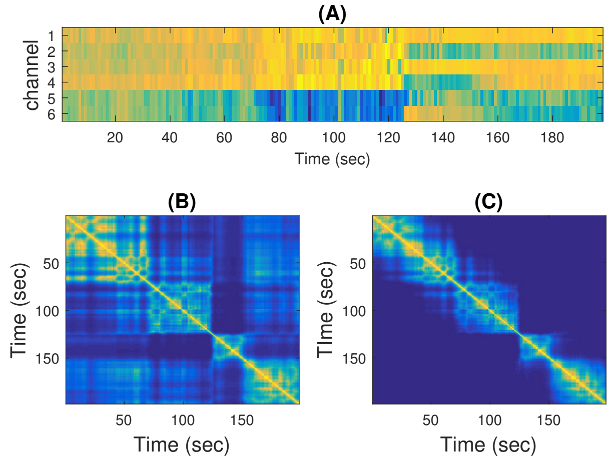

Fig. 2. A: The sequence of eigenvector centralities (EVCs) over time computed from 6-channel iEEG signals. B: original similarity matrix. C: similarity matrix with temporal constraint. The seizure is start at the 61 seconds and end at the 137 seconds.

3. EXPERIMENTAL RESULTS

In this section, experiments are carried out to verify the effectiveness of our method. The experiments include three parts: (1) we visualize the influence of the temporal constraint on the similarity computation; (2) we introduce an evaluation criterion to analyze the results; (3) we compare the segmentation performance among Gaussian temporal-constrained clustering method, constant temporal-constrained clustering method, k-medoids and k-means.

3.1. Dataset and Settings

The Freiburg dataset which contains iEEG recordings of 21 patients suffering from intractable focal epilepsy is used to evaluate the methods. The channel number of the iEEG data is 6 and the sampling rate is 256Hz. The iEEG signals called ictal and interictal which contain seizure onset data and preictal data are available for each patient. In our experiment, the data we used are clipped from 60 seconds prior to seizure onset to 60 seconds after seizure ends. Thus, each period of our experimental data contains a pre-ictal state, an ictal state, and a post-ictal state. We take 13 seizures from 4 patients (patient 1-4). In the computation of connectivity matrices, the window slides along the time axis with a stride of 1 second, thus there is no overlap between adjacent sub-segments. The number of clusters is set as 3, because pre-ictal, ictal, post-ictal are primary states and other refined states are not to be discussed in our experimental data. The parameter σ^2 is set to 500 and L is set to 30.

3.2. Similarity Matrix Visualization

In the similarity matrix computation, the sequence of EVCs: $\{EVC_{t_i}\}, i = 1, 2, ..., N$ has N samples which take pairwise computation. For $N * N$ similarity matrix S, all the entries in S are greater than 0 and the diagonal entries are equal to 1. A sequence of EVCs is shown in Figure 2A. Figure 2B shows the original similarity matrix computed from 2A without the temporal constraint. The similarity matrix example which is restricted by temporal relation is demonstrated in Figure 2C. It is clear that the values in similarity matrix are suppressed in the bottom left corner and upper right corner in Figure 2C. These small values reflect that EVCs at these positions are less similar after adding temporal constraint. Thus, the similarities are reduced between the EVCs with long time intervals.

3.3. Evaluation Criteria

In the segmentation, we associate the EVCs with clustering labels, which could be formulated as below

$$l_i = L(EVC_{t_i}), \tag{5}$$

where $L(.)$ denotes the clustering algorithm and for convenience we use labels taken from positive integer. So we get the following formulation:

$$l_i \in \{1, 2, ..., K\}, \tag{6}$$

where K is the number of clusters. For evaluation, we employ precision and recall criteria similar to other segmentation tasks:

$$Recall = \frac{TP}{TP + FN}, \tag{7}$$

$$Precision = \frac{TP}{TP + FP}, \tag{8}$$

where TP (true positives) represents the number of EVCs during seizure detected by our method correctly, FP (false positives) represents the number of EVCs not during seizure wrongly detected by our method and FN (false negatives) represents the number of EVCs during seizure not detected by our method. The F1 score is used in our experiments too, which is the harmonic mean of precision and recall.

To evaluate the performance of the clustering results for temporal segmentation tasks, we propose a new evaluation criterion STV(.), which is inspired by the total variation (TV) [17] of a sequence Eq.(9).

$$TV(\mathbf{l}) = \sum_{i=1}^{N} |l_{i+1} - l_i|, \tag{9}$$

The value of TV is the variation of the states along the time dimension. The more variation between adjacent states means

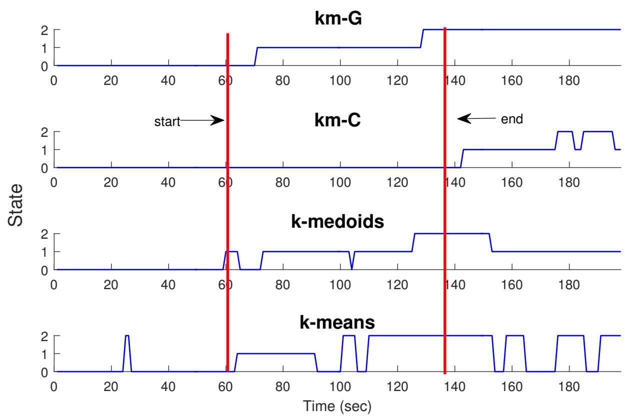

Fig. 3. The epileptic states segmented by k-medoids with Gaussian temporal constraint, with constant temporal constraint, without temporal constraint and k-means. The seizure is start at 61 seconds and end at 137 seconds, which is marked by two red line. Three corresponding epileptic states are: pre-ictal, ictal, post-ictal, which are labelled by state0, state1 and state2.

the greater TV value. But the calculation of TV is not suitable for our segmentation tasks because the l_i is just a sign not a value. In our task, we modify this function as below:

$$STV(\mathbf{l}) = \frac{\sum_{i=1}^{N} |sgn(l_{i+1} - l_i)| - K + 1}{N - K}, \qquad (10)$$

where we use the function $STV(.)$ to denote this new score and the $sgn(.)$ denotes the sign function. The $STV(l)$ is in $[0, 1]$ and lower value means the better performance.

3.4. Comparison of Performance

In this experiment, we compare the performance among the k-medoids with Gaussian temporal constraint (km-G), the k-medoids with constant temporal constraint (km-C), k-medoids and k-means. First, we analyze the results of state segmentation by the four methods in a seizure which is shown in Fig 3. From this figure, we could find that the states clustered by k-medoids and k-means methods are unstable because there are many obvious clustering states jumping in small time intervals. While the results of km-G method do not have the sudden hopping states and 3 states are clearly segmented over time. Moreover, the segmented seizure onset state is in agreement with the actual time and the clustering results are continuous in each state, which keep the temporal integrity and consistency and are much better than other results. More experimental results will be discussed below.

To quantitatively evaluate the comparison performance in all experimental data, we use the evaluation criteria above and the comprehensive performance comparison is presented in Table 1. From the table, we could find km-G achieve the best recall, F1 and STV results and the recall is almost two times

Table 1. Segmentation performance .

Method	km-G	km-C	k-medoids	k-means
Recall	**84.48%**	8.62%	22.41%	20.69%
Precison	**27.07%**	3.60%	13.83%	15.19%
F1	**41.00%**	5.08%	17.11%	17.53%
STV	**0.01**	0.06	0.10	0.09
Recall	**59.61%**	31.20%	37.60%	38.16%
Precision	89.17%	**98.25%**	77.59%	76.54%
F1	**71.45%**	47.36%	50.66%	50.93%
STV	**0.00**	0.01	0.08	0.07
Recall	**60.42%**	59.72%	46, 53%	3.74%
Precision	88.78%	85.15%	**90.54%**	33.33%
F1	**71.90%**	70.20%	61.47%	6.29%
STV	**0.00**	0.01	0.05	0.09
Recall	**70.59%**	36.97%	32.49%	34.17%
Precision	**87.80%**	86.84%	54.72%	69.32%
F1	**78.26%**	51.87%	40.77%	45.78%
STV	**0.00**	0.01	0.06	0.06

$\star$ 4 group of performance criteria values are obtained by experimenting on data of 4 patients respectively.

higher than other methods in all data. Though, km-C and k-medoids respectively obtain a little better precision value (98.25%, 90.54%) than km-G (89.17%, 88.78%) in two cases, their corresponding recall values are low. Thus, km-G only suffers insignificant performance drop on precision in these two cases. We could also find that km-G and km-C methods obtain better STV results than k-medoids and k-means, which means temporal constraint is helpful to keep the states continuous. Besides, we could also find km-G method suppress more noise than other methods by achieving the best STV value, which can be also verified from Fig 3. From the discussion, we could find km-G method outperform other methods and is effective for epileptic states segmentation.

4. CONCLUSION

In this paper, we consider the epileptic states segmentation method with temporal constraints. With the temporal information, this method suppresses the noise and enhances features of signals over time and improves the segmentation performance. The new performance criterion STV describing the temporal integrity and consistency is helpful to analyze the results of segmentation in practice. The experimental results show the effectiveness of the k-medoids method with Gaussian time constraint.

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