# EPILEPTIC STATE SEGMENTATION WITH TEMPORAL-CONSTRAINED CLUSTERING

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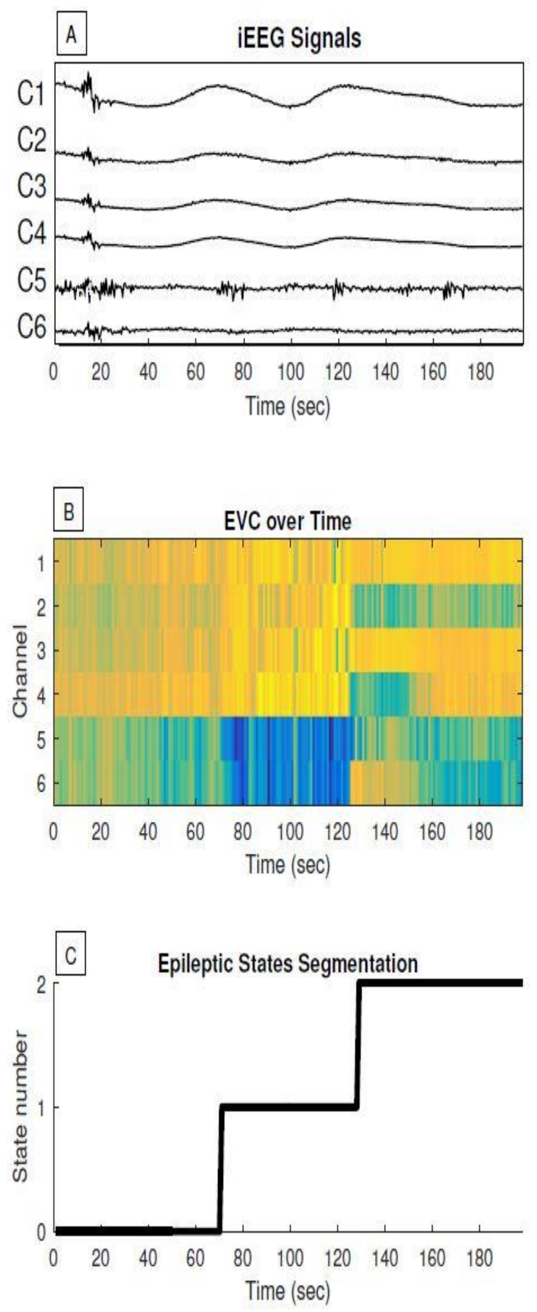
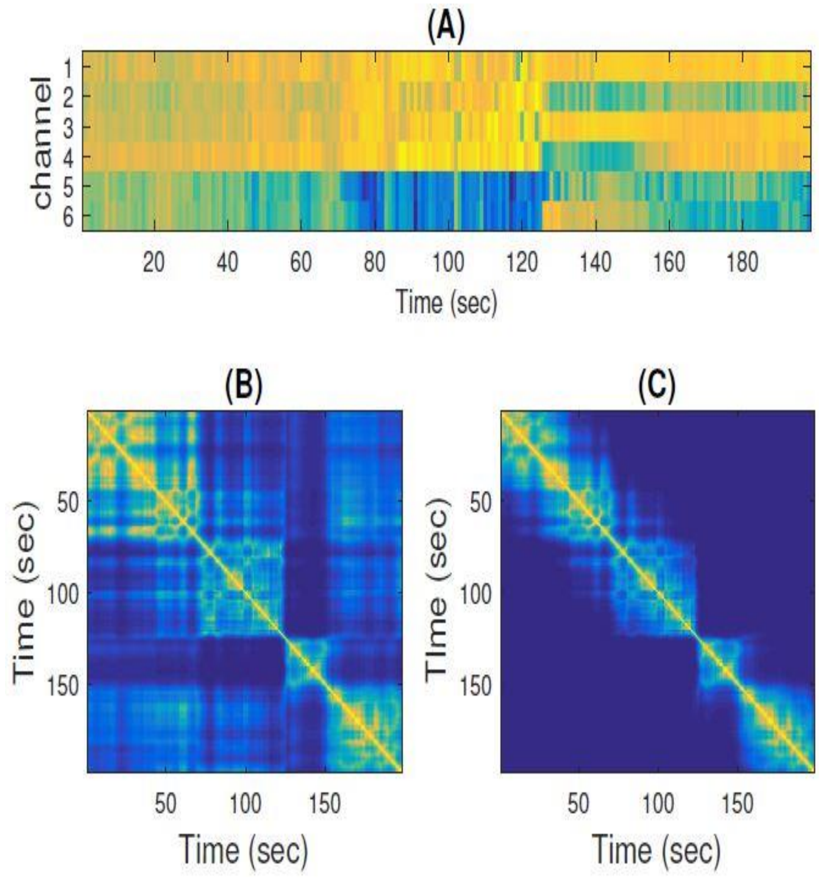
## Epileptic State Segmentation




- A: A sample of iEEG signals recording with 6 channels.
- B: The time-variant signal features (EVCs) of signals in A.
- C: The state segmentation result of signals in A. This seizure start at the 61 seconds and end at the 137 seconds.

- 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.

## Why? & How to Fix It?




**What can we do?**

- We consider the following two aspects to add the temporal constraint to clustering method.
- 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.
- A good choice : **Adding temporal constraint.**

- 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.

**Using temporal information, the noises could be effectively suppressed and robust clustering performance is achieved**

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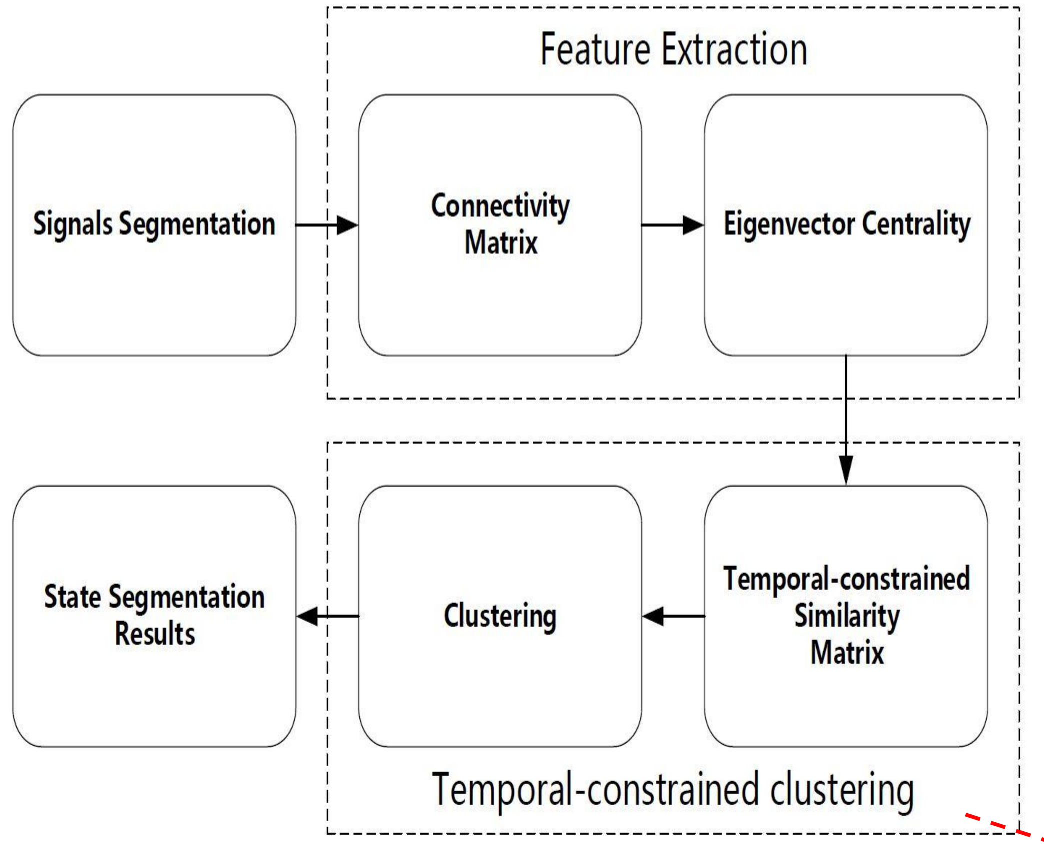
## Our Method




The framework of our method

### Signal Feature Extraction

- Coherence is a widely used measure to compute the functional connectivity between signals.

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

- where P denotes the spectral density function.
- The eigenvector centrality (EVC) is the leading eigenvector centrality corresponding to C and $\lambda_{max}$ is the maximum eigenvalue of this matrix.

$$C * EVC = \lambda_{max} * EVC.$$

### Similarity Matrix Computation with Temporal Constraint

The similarity $S_{t_i,t_j}$ between $EVC_{t_i}$ and $EVC_{t_j}$ with Gaussian temporal constraint and constraint temporal constraint could be formulated as below:

- The Gaussian temporal constraint:

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

- The constant temporal constraint:

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

### Epileptic States Segmentation

In the MCC-based robust autoencoder, the reconstruction loss function is formulated as:

- K-medoids
- K-means

## Experimental Results

### Evaluation Criteria

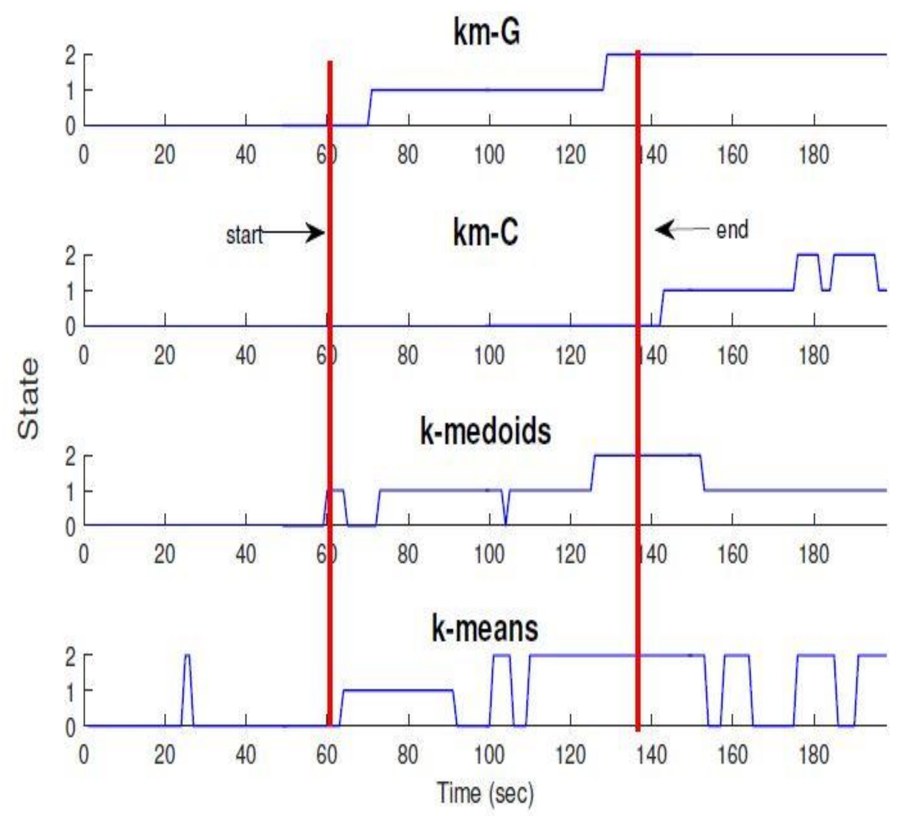
- Recall
- Precision
- Signed total variation: a new criterion for our segmentation tasks.

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

- 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.

### Comparisons – *Segmentation performance*

Comparison with 4 methods




- Comparison methods: **(1) km-G: k-medoids with Gaussian temporal constraint, (2) km-C: k-medoids with constant temporal constraint, (3) k-medoids, (4) 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: preictal, ictal, post-ictal, which are labelled by state0, state1 and state2.

**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 |

⋆ 4 group of performance criteria values are obtained by experimenting on data of 4 patients respectively.

## Conclusion & Acknowledgements

- 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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