Application of Topological Data Analysis to Delirium Detection

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Abstract

We propose a new scoring algorithm for detecting delirium from one-channel EEG, based on Topological Data Analysis. Numerical experiments demonstrated that our method achieved higher predictive performance than the other existing methods.

1 Introduction

Delirium is a mental state where somebody becomes excited and not able to think or speak clearly [5]. Delirium is dangerous and common among elderly inpatients but is difficult to be diagnosed manually [3]. Therefore, there is a demand for an automated method of delirium detection using electroencephalogram (EEG). Recently, detecting delirium from one-channel EEG has attracted much attention because one-channel EEG can be measured with ease. Several delirium detection algorithms based on frequency analysis have been proposed in [6, 10].

In this paper, we propose a novel scoring algorithm based on Topological Data Analysis (TDA) for detecting delirium. TDA is an approach to analyze datasets with topology [1, 2, 13] and it has been successfully applied to time-series analysis [7, 9, 11, 12]. With time-delay embedding and persistent homology, we define a new score called TDA-EEG that evaluates signs of delirium from EEG. Our numerical experiments demonstrated that our method could detect delirium from one-channel EEG, which achieved high prediction performance.

2 Methodology

Given a set of EEG signals, we first preprocess them and remove signals shorter than 60 seconds. Then we split the remaining signals into 30 ones whose length are two seconds. For each patient, we define the TDA-EEG score by the following procedure:

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1. Construct the time-delay embedding of the preprocessed EEG signal to convert it into a point cloud in the three-dimensional Euclidean space.
2. Calculate the persistence diagram of the Vietoris-Rips complex associated with the point cloud.
3. For the persistence diagram, keep the points whose distances to the diagonal are larger than a given threshold.
4. Compute the sum of the distances to the diagonal of the remaining points.
5. Define the TDA-EEG score of the target patient as the average of the sums for 30 signals of length two seconds.

If the TDA-EEG exceeds a given threshold, the state of the patient is regarded as delirium.

3 Numerical Experiments

We report the results of our numerical experiments and discuss the performance of our TDA-EEG. In this experiment, we used the EEG dataset measured from 137 resident participants in University of Iowa Hospitals and Clinics. This dataset consists of 58 positive (cased) and 79 negative (control) patients. When we construct the time-delay embedding in our method, we set the delay and skip parameter to be 60 ms and 6 ms, respectively. For comparison, we used the two existing algorithms in [6, 8] and Adaboost [4]. The two existing algorithms in [6, 8] calculate scores based on frequency analysis. For Adaboost, we calculate each patient's score with a model trained by the other patients. See Appendix B for details of these existing methods.

Table 1 shows the results of AUC and specificity in the case where the sensitivity $= 0.75$. From Table 1, we can observe that our TDA-EEG achieved the highest AUC scores among the four methods. In addition, the specificity of TDA-EEG is 0.71, which is also the highest score. We show the ROC curves of the four methods in Figure 1. Figure 1 suggests that TDA-EEG generally attained higher true positive rates than the other methods.

Table 1: AUC and specificity of each method

	TDA-EEG	Shinozaki *et al.* [10]	Numan *et al.* [6]	Adaboost
AUC	**0.80**	0.72	0.66	0.69
Specificity (Sensitivity = 0.75)	**0.71**	0.52	0.42	0.50

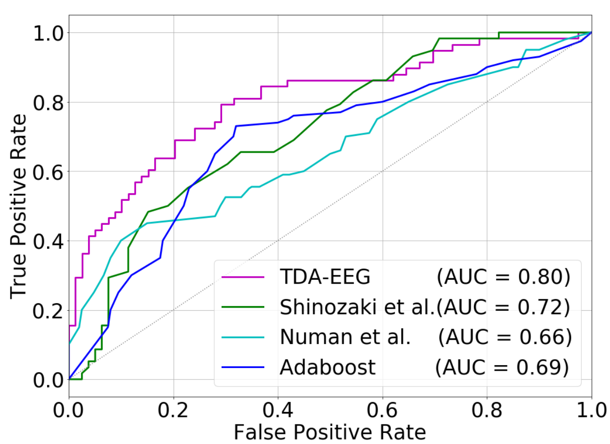

Figure 1: ROC curve of each method

According to the previous study [11], time-series analysis via TDA are robust to noises because it extracts topological features of a time-series signal from the time-delay embedding. In our experimental results, such robustness would lead to achieving high AUC.

We show some examples of EEG signals in Figures 2 and 3. Both Figures 2 and 3 are EEG signals of positive cases. For Figure 2, both Shinozaki *et al.* [10] and TDA-EEG showed positive scores when we set sensitivity $= 0.75$. For Figure 3, while Shinozaki *et al.* [10] showed negative score, our TDA-EEG showed positive score correctly. Comparing with Figure 2, we find that the signal shown in Figure 3 is highly volatile. Since Shinozaki *et al.* [10] calculates a score only depending on the spectrum 3 Hz by that of 10 Hz, there is a risk to overlook delirium correctly from such a signal. In contrast, since our method depends not only on frequency but also on topological features from signals, it can detect delirium even when signals are highly volatile.

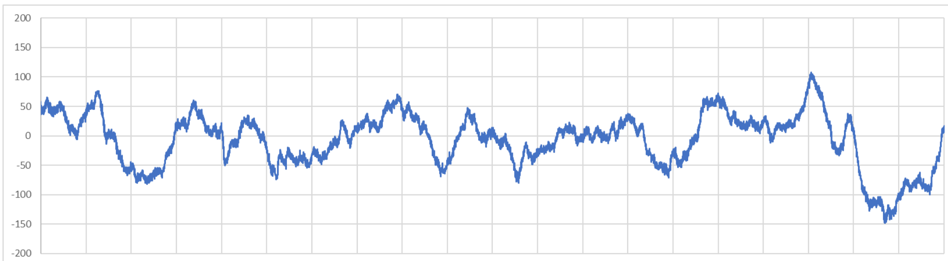

Figure 2: Example of EEG signal of positive case

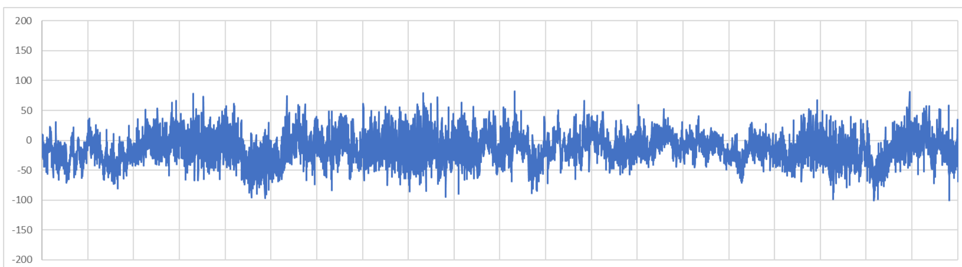

Figure 3: Example of EEG signal of positive case

4 Conclusion

In this paper, we proposed a novel scoring algorithm to detect delirium based on TDA from one-channel EEG. The numerical experiments demonstrated that our method achieved higher predictive performance than the existing methods. Since detecting delirium only with one-channel EEG signals is strongly required in practice, our method broadens the feasibility of delirium detection.

For future work, we plan to validate the effectiveness of our proposed method in more realistic situations. In addition, we believe that the potential applications of the method are not limited to the use in medical fields. For example, it would be interesting to apply our method to other time-series signals such as gyro sensor data or vibration data.

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A Details of Existing Methods

Figure 4 is an example of EEG signal of negative cases that both Shinozaki *et al.* [10] and TDA-EEG returned scores correctly.

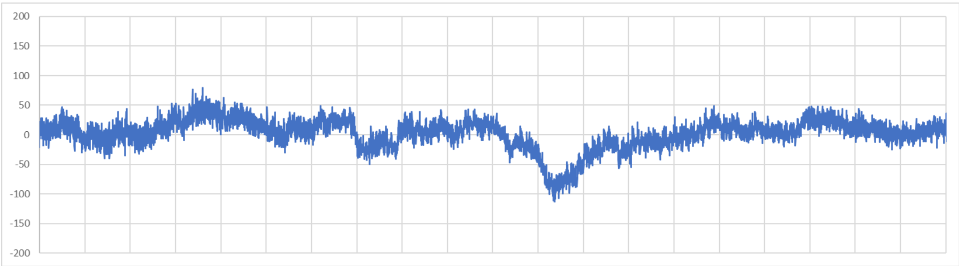

Figure 4: Example of EEG signal of negative case

B Details of Existing Methods

In this section, we describe the details of existing methods for detecting delirium [10, 6].

Shinozaki *et al.* [10] proposed a score calculated as follows:

1. Compute the power spectra of 3 Hz and 10 Hz of the input EEG signal.
2. Define the BSEEG score as the ratio of the spectrum 3 Hz by that of 10 Hz.

Numan *et al.* [6] proposed a score calculated as:

1. Compute the power spectra of 1 Hz and 6 Hz of the input EEG signal.
2. Define a score as the ratio of the spectrum 1 Hz by that of 6 Hz.

For Adaboost, we calculate a score for each patient as follows:

1. Train a model with the other patients's data.
2. Apply the model to 30 signals of the patient and predict their labels.
3. Calculate a score of the patient as the ratio of the number of positive labels the model output.