Epileptogenic focus detection in intracranial EEG based on delay permutation entropy

Guohun Zhu, Yan Li, Peng Paul Wen, Shuaifang Wang, and Min Xi

Citation: AIP Conference Proceedings **1559**, 31 (2013); doi: 10.1063/1.4824993
View online: http://dx.doi.org/10.1063/1.4824993
View Table of Contents: http://scitation.aip.org/content/aip/proceeding/aipcp/1559?ver=pdfcov
Published by the AIP Publishing

Epileptogenic Focus Detection in Intracranial EEG based on Delay Permutation Entropy

Guohun Zhu[a,b.c], Yan Li [a,b], Peng (Paul) Wen[a,b], Shuaifang Wang[a,b] and Min Xi[c]

[a]*Faculty of Health, Engineering and Science, University of Southern Queensland, Toowoomba, QLD 4350, Australia*
[b]*Centre for Systems Biology, University of Southern Queensland Toowoomba, QLD 4350, Australia*
[c]*School of Electronic Engineering and Automation, Guilin University of electronic technology No.1 Jinji Road, Guilin, Guangxi 541004, China*

Abstract. Epileptogenic localization is a critical factor for successful epilepsy surgery. Determining the epileptogenic hippocampus with single channel intracranial electroencephalography (iEEG) recording is beneficial to decrease the risk of infection compared with that based on multi-channel iEEGs. Delay permutation entropy (DPE) methodology is presented in this study to measure iEEG with different delay lag based on focal epileptogenic zone. A total of 1600 20-s epileptic iEEG are evaluated and are used as features to classify epileptogenic and non-epileptogenic zone. Experimental results show that the DPE index of epileptogenic iEEG is significant lower than that of non-epileptogenic hemisphere when delay lag ranges from 5 to 30 ($p=0.01$). In addition, the accuracy of identifying epileptogenic region with the DPE index is increased when the delay lag between 5 and 25, compared to the performance of the PE index.

Keywords: DPE, iEEG, Epileptogenic, focus localization, support vector machine.
PACS: 87.85.Ng.

INTRODUCTION

There are about 1% population in the world are diagnosed as epilepsy [1]. Patients with drug-resistant epilepsy can turn to surgery. Therefore, how to localize the region of seizure onset precisely is very important in the treatment. Intracranial EEG (iEEG) is a useful to localize the epileptogenic zone. However, epileptogenic focus localization based on multi channels intracranial iEEG is time-consuming and increases the risk of infection. Therefore, using one channel iEEG recording to diagnose the seizure onset zone is an important research issue.

Many pre-surgical evaluations have been studied on epilepsy, such as magnetic resonance imaging (MRI) [2], positron emission tomography (PET) [3] and ictal single photon emission computed tomography (SPECT) [4]. They correctly localize the epileptic area with approximately ~50-80% accuracy of the cases depending on the presence or absence of a structural lesion [5-7]. Recently, Andrzejark et al. [8] has shown that iEEG signals from epileptogenic zone are less random, more nonlinear-

2013 International Symposium on Computational Models for Life Sciences
AIP Conf. Proc. 1559, 31-36 (2013); doi: 10.1063/1.4824993

dependent than those from non-epileptogenic area using a combined surrogate analysis method.

This paper proposes delay permutation entropy (DPE) method to classify the epileptogenic zone signals from non-epileptogenic zone signals based on only one channel of iEEG signal. Permutation entropy (PE) is introduced by Bandit and Pompe [9] to estimate the complexity of time series. PE has been applied to predicate epileptic seizures on animal iEEG by Li et al [10]. Bruzzo et al. [11] found that PE was poor to predict the seizure on scale EEGs but could be possible useful for vigilance detection on epilepsy patients. The DPE improves the nonlinear detection performance of PE on moving-average processing time series by Matilla-García [12]. This paper is the first time to apply the DPE to real-world time series, especially on epilepsy iEEG data.

This paper is organized as follows: the experimental data are briefly introduced in the next section. The proposed DPE algorithm is showed in Section 3. Section 4 presents the experimental results. Finally, conclusions are drawn in Section 5.

THE EXPERIMENTAL DATA

The experimental data used in this paper were obtained from the public Bern-Barcelona EEG database (http://www.dtic.upf.edu/~ralph/sc/) collected from ten patients. The database includes two distinct sets: one comes from epileptogenic zone (set F) and the other is recorded from brain areas that were not involved in seizure onset (set N). The sample rate is 512 Hz if the number of record is less than 64 channels. Otherwise, it is 1024 Hz. Each data contains two signals, signal x is the patient's focal EEG channel and signal y is the neighboring channel of the epileptogenic zone. Each signal in each recording has 10240 data points. The detailed description and usage of this database can be found in [8].

This study applies two sub sets of Bern-Barcelona EEG database. The sizes of these datasets are 100 and 1500 recordings respectively. The small set is named #50 which is a sample data used by [8], and the large set is denoted as #750 which include recording from No. 751 to No. 1500.

THE METHODOLOGY

The procedure of the proposed method is shown in Fig.1. Note that the PE and DPE index features are extracted separately. The SVM involves the training stage and the testing stage, with the size of the training data equals to the size of the testing sets.

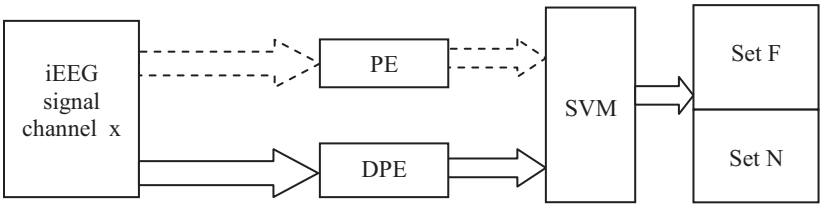

FIGURE 1. Algorithm diagram.

Delay Permutation Entropy Method

The DPE is an improved method for detecting nonlinear structural based on PE method. The DPE is also a measurement for the delay lags δ of an epileptic EEG time series $\{x_t\}_{(t=1,\cdots,n)}$. The DPE algorithm is outlined as follows [12].

1. Construct an embedded m-dimensional space X_m as follows:

$$X_m(t) = \{x_{t+\sigma}, x_{t+2\sigma}, \cdots, x_{t+m\sigma}\} \qquad 1 \le t \le (n - \sigma m + 1)$$

2. Arrange each vector of X_m to an increasing order

$$X_i(t) = \{x_{t+j_1} \le x_{t+j_2} \le \cdots \le x_{t+j_m}\}$$

Let $\pi_i = \{j_1, j_2, \cdots, j_m\}$, then π_i is a symbol of m! possible permutations of the vector of $\{1, 2, \cdots, m\}$.

3. From *i=1* to *N-m* calculate each $x_i(t)$ into symbol π_i.
4. Let $p(\pi_i, \delta)$ be the probability distribution of π_i.
5. Calculate the Shannon entropy of all the symbols

$$h(m,\delta) = -\sum_{i=1}^{n-\delta m+1} p(\pi_i,\delta) \ln p(\pi_i,\delta)$$

According to the PE algorithm in [9], PE is a special case of DPE, where $\delta=1$. During this study, it assigns *m=4* and *n=10240*.

Support Vector Machine

To measure the performance of the DPE features from sets F and N with different delay lags δ, a support vector machine (SVM) is selected to conduct the binary classification. The SVM has been successfully used in EEG classification [13]. It can perform both the linear space discrimination and nonlinear classification by choosing different "kernel" functions which can be linear, polynomial kernel, radical basis function (RBF) and sigmoid. In this paper, the SVM algorithm with RBF kernel is implemented in R package e1071 [14].

THE EXPERIMENTAL RESULTS

To evaluate the performance of the methods in Section 3, the DPE algorithm is implemented in C program language, while the SVM and statistical analysis are implemented by R. The software is available at http://brain-graph.appspot.com. The experiments include two parts: (1) analysing DPE index associated with epileptic iEEGs under different delay lags; (2) evaluating classification accuracy of the DPE features by different lags on two different sizes of data sets.

Both experiments investigate the data sets #50 and #750 and the value of δ ranges from 1 to 50.

Statistical analysis on the relation between DPE index and δ

Fig.2 shows the relation between different δ and the DPE index associated with channel x of epileptogenic zone iEEG and non-epileptogenic area iEEGs on two datasets. In order to evaluate the relation between the DPE index and δ, the value of δ changes from 1 to 30.

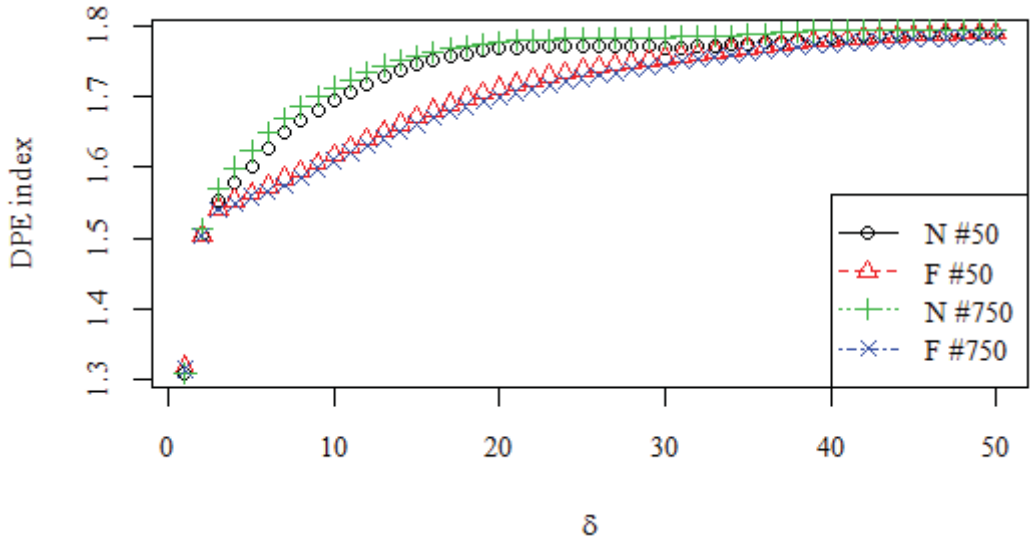

FIGURE 2. The relation between the DPE index and δ on iEEG channel x

To make the relation between DPE index and δ more clear, comparison between DPE index of epileptogenic iEEG and those of non-epileptogenic signal are employed with the Student's test. Two ranges of δ are measured based on data set #750. The first range is 1 ~30, the statistical DPE indices between sets F and N are not significantly different ($p=0.08$). The second range is 5 ~30, and the statistical difference are considered significant ($p=0.01$).

Evaluating the relation between δ and classification accuracy

This section is to investigate the relation between classification accuracy and δ when one dimension DPE index is applied to identify the epileptogenic iEEG. Firstly, each recorded signal x is extracted with DPE indices with δ from 1 to 50. For set #50, total 100×50 dimensional DPE features are extracted, and for set #750, there are 1500×50 dimensional DPE indices are also extracted. Each dimensional feature is forwarded into a SVM to conduct classification, where the odd indices of instances are used for training and the remaining features are used for testing. Finally, the relation of the accuracies and δ on two EEG data sets are obtained and illustrated in Figure 3.

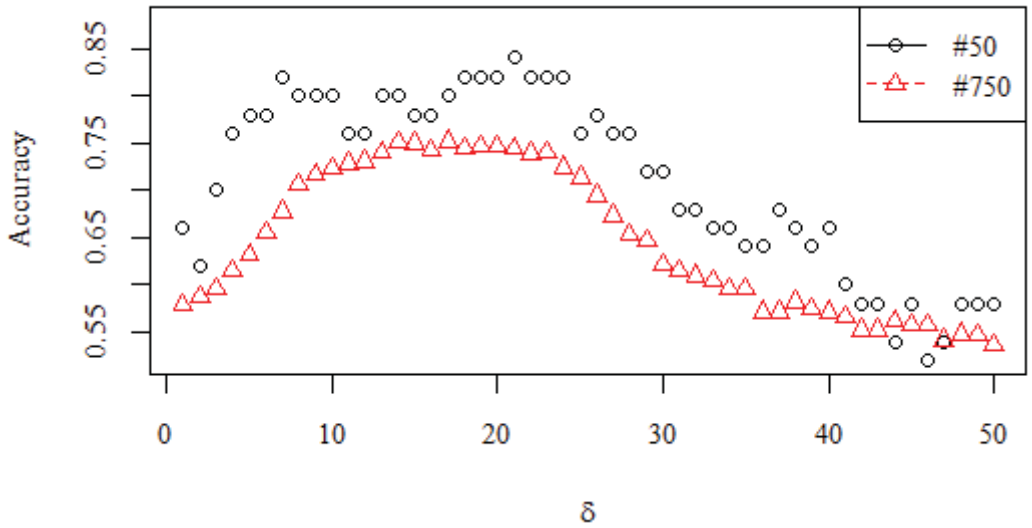

FIGURE 3. The relation between accuracy and δ of DPE on iEEG channel *x* for the identification of epileptogenic and nonepilptogenic

Based on Figure 3, the maximum accuracy is 0.84 for the EEG set #50 and δ is selected as 21, while the maximum accuracy is 0.75 when EEG set is #750 and δ is assigned as 17. In addition, the accuracies are increased when δ is located between 5 and 25.

To be more clear, a confusion matrix between the experts scoring and automatic classification based on PE ($\delta=1$ of DPE) is shown in Table 1. The accuracy is 66%.

TABLE 1. Classification accuracy with PE features.

	Set F	**Set N**
Set F	15	7
Set N	10	18

The confusion matrix based on the DPE index ($\delta=21$) is shown in table 2.

TABLE 2. Classification accuracy with DPE index with $\delta=21$.

	Set F	**Set N**
Set F	22	5
Set N	3	20

The accuracy of Table 2 is 84%. According to Tables 1 and 2, the classification accuracy based on DPE index is 18% higher than that based on PE. More importantly, the highest accuracy based on the DPE index in this study is higher than the existing recorded results, which is ~50-80% [5-7]. This proposed method exhibits that DPE indices can be potentially applied in epileptogenic focus location based on the iEEG signals.

CONCLUSION

In this paper, the DPE index is applied to identify the epileptogenic focus localization. This paper is the first time to study the epileptic iEEG with DPE index. Meanwhile, there is no researcher conducting classification with single channels iEEG data between epileptogenic zone and non-epileptogenic brain area so far as we known. It is found that the DPE index of epileptogenic zone iEEG is significant lower than those in non-epileptogenic when the delay lag changes from 5 to 30 ($p=0.01$).

Based on the analysis of the relation between the delay lag and the DPE index, the DPE indices are forwarded to a SVM to identify the epileptogenic zone. The classification results show that the accuracy detecting epileptogenic with the DPE index is increased when the delay lag is between 5 and 25 compared to that of the PE index.

It is noted that the proposed method does not use surrogate data compared with the study by Andrzejark et al. [8], and only one dimensional feature is enough to obtain 84% accuracy based on the DPE index with $\delta=21$, which is 18% higher than that based on the PE index. This indicates that the proposed method in this study is not only high accuracy and also fast. Hence, the DPE index can be a potentially suitable candidate for diagnostic protocol to identify the epileptogenic region.

ACKNOWLEDGEMENTS

We would like to express our sincere gratitude and appreciation to the reviewers from CMLS 2013 for their feedback and suggestions on our paper.

REFERENCES

1. F. Mormann, R. G. Andrzejak, C. E. Elger and K. Lehnertz, *Brain* 130 (2), 314-333 (2007).
2. M. Seeck, F. Lazeyras, C. M. Michel, O. Blanke, C. A. Gericke, J. Ives, J. Delavelle, X. Golay, C. A. Haenggeli, N. de Tribolet and T. Landis, *Electroencephalography and Clinical Neurophysiology* 106 (6), 508-512 (1998).
3. I. Savic, J. O. Thorell and P. Roland, *Epilepsia* 36 (12), 1225-1232 (1995).
4. M. R. Newton, S. F. Berkovic, M. C. Austin, C. C. Rowe, W. J. McKay and P. F. Bladin, *Journal of Neurology*, Neurosurgery & Psychiatry 59 (1), 26-30 (1995).
5. M. V. Spanaki, S. S. Spencer, M. Corsi, J. MacMullan, J. Seibyl and I. G. Zubal, *Journal of nuclear medicine : official publication*, Society of Nuclear Medicine 40 (5), 730-736 (1999).
6. T. R. Henry and R. L. Van Heertum, *Seminars in Nuclear Medicine* 33 (2), 88-104 (2003).
7. R. C. Knowlton, R. A. Elgavish, A. Bartolucci, B. Ojha, N. Limdi, J. Blount, J. G. Burneo, L. Ver Hoef, L. Paige, E. Faught, P. Kankirawatana, K. Riley and R. Kuzniecky, *Annals of Neurology* 64 (1), 35-41 (2008).
8. R. G. Andrzejak, K. Schindler and C. Rummel, *Physical Review E* 86 (4), 046206 (2012).
9. C. Bandt and B. Pompe, *Physical Review Letters* 88 (17), 174102 (2002).
10. X. Li, G. Ouyang and D. A. Richards, *Epilepsy Research* 77 (1), 70-74 (2007).
11. A. Bruzzo, B. Gesierich, M. Santi, C. Tassinari, N. Birbaumer and G. Rubboli, *Neurol Sci* 29 (1), 3-9 (2008).
12. M. Matilla-García and M. Ruiz Marín, *Economics Letters* 105 (1), 1-6 (2009).
13. G. Zhu, Y. Li and P. P. Wen, in *Brain Informatics*, edited by F. Zanzotto, S. Tsumoto, N. Taatgen and Y. Yao, Springer Berlin Heidelberg, 2012, Vol. 7670, pp. 185-195.
14. A. Karatzoglou, D. Meyer and K. Hornik, *Journal of Statistical Software* 15 (9), 1-28 (2006).