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Accurate Multiscale Permutation Entropy Analysis of Brain Rhythm to Detect Epileptic Seizure

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ABSTRACT

Electroencephalogram(EEG) has been a standard tool to monitor the status of the brain. For quantification of EEG, permutation entropy has been of interest due to simplicity and robustness to noise. A multiscale extension of PE, called multiscale PE(MPE), has been promising in fully describing the dynamical characteristics of EEG over multiple temporal scales. However, an imprecise estimation of MPE at large scales limits its application for analyzing of short EEG. Here, a new multiscale PE measure which aims at estimating entropy accurately is presented. By computing PE of all possible coarse-grained time series and averaging the values of PE at each scale, the resultant composite MPE (CMPE) yields improved accuracy in estimation of entropy. Thus, the CMPE measure accomplishes consistent quantification of entropy regardless of the length of data. This advantage of CMPE renders its capability for analyzing EEG signals. Through simulations with two synthetic noises, CMPE has proved its capability over MPE in terms of accuracy. Experimental results using normal, inter-ictal and ictal EEG recordings have shown that the CMPE measure has leaded an improved discrimination capability for three different neurological states (normal, inter-ictal, and ictal states) than the conventional PE family.

KEYWORDS: Electroencephalogram (EEG), Composite multiscale permutation entropy, Epilepsy, Seizure

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1. Introduction

Epilepsy is a chronic disorder of the central nervous system that predispose individuals to experiencing recurrent seizures [1]. A seizure is a sudden, transient aberration in the brain's electrical activity which yields disruptive symptoms. Approximately 40 or 50 million people world-wide are diagnosed with epilepsy and it is one of the most common neurologic disorders [2]. Computerized seizure detection will enable the engineering of novel therapeutic and alerting systems that may ease the burden of intractable seizures. Seizure detection is most often accomplished through analysis of the brain rhythm, namely, electroencephalogram (EEG). EEG is a recording of the electrical activity generated by collections of neurons within the brain, thus containing a lot of information about the condition of the brain. The development of quantitative EEG analysis was motivated by the need for objective measures as well as some degree of automation in case of the brain disorder.

Over the past decade, the most common quantitative EEG analysis is frequency analysis, which is based on an assumption of stationarity of a signal. Recently, considering the nonlinear and nonstationary nature of EEG signals, a number of time-frequency analysis have been widely applied to analysis of EEG, which include the short time Fourier transform [2], the wavelet transform [4], the multiwavelet transform [4, 5], and so on. However, the time-frequency analysis methods, which decompose the signal into several stationary monocomponent signals, fail to reflect the dynamic changes of EEG signals effectively.

An alternative for dealing with nonlinear and nonstationary EEG signals put emphasis on nonlinear parameter such as entropy. Entropy is a measure of the complexity or the regularity of a signal, which is capable of describing nonlinear dynamics of a signal. A reduction in entropy has been often observed in case of an abnormal state of the brain [6]. One of the most widely used entropy measures is the sample entropy (SampEn) [7, 8]. SampEn accounts for the correlations of two consecutive sequences in a sense that two sequences similar to each other for the first points remain similar at the next points. SampEn has shown its capability in representing the regularity of EEG signals under several clinical cases [9]. More recently, permutation entropy (PE) has been developed for measuring the regularity for nonstationary and noisy time-series [10, 11]. Since it is based on comparison of neighboring values, the computation of PE is simple, robust against noise, and suitable for online monitoring. Also, PE has been promising tool for analyzing EEG signals without a restriction on model [11]. However, PE is based on single scale computation like SampEn, thus fail to represent the characteristics across multiple temporal scales.

To measure the entropy of time-series over multiple time scales, multiscale based entropy measures have been of interest, which are based on a coarse-graining procedure and following estimation of SampEn or PE, referred to as multiscale entropy (MSE) or multiscale PE (MPE), respectively [12, 13]. Among those, MPE has proved its effectiveness in describing the dynamic changes of EEG signals by benefitting the merits from both a multiscale approach and PE. It was found that MPE is more robust than MSE in that it is more robust in the presence of artifacts and observational noise. In [14], MPE has exhibited the promising result for detecting epileptic EEG recordings.

In this paper, to address this unreliable estimation of MPE, a more accurate MPE is presented. The proposed MPE makes use of all available coarse-grained time-series, followed by averaging of PE of all coarse-grained time-series at each scale, which is referred to as composite MPE (CMPE). Through the simulations using two synthetic noise signals, i.e., white and noises, the proposed CMPE showed an improved accuracy over the conventional MPE in that it has provided less variance of entropy estimation, especially at large scale. Next, CMPE was applied to the actual normal and epileptic EEG recordings to validate its effectiveness in detecting seizure and epilepsy compared to MPE.

The remainder of this paper is organized as follows. Section 2 introduces PE, MPE, and the proposed CMPE. In the Section 3, CMPE is applied to the experimental EEG signals and some comparisons with MPE are provided. Finally, Section 4 concludes this study.

2. Methods

2.1 Permutation Entropy (PE)

PE is a measure of dynamic changes of a time series by comparing neighboring values [11]. The time series is transformed into a series of ordinal patterns which describes the order relations between the present values and a fixed number of equidistant values at a given past times. Based on the counting of ordinal patterns, called motifs, PE quantifies the relative frequencies of the distinct motifs. Since the computing of PE considers just ordinal patterns not the amplitude of the time series, thus it leads to robustness against measurement noise.

Consider a time series, $\{x(i), i = 1, ..., N\}$ with length N. By carrying out an embedding procedure, it forms vectors of length m, $X(i) = [x(i), x(i+\tau), ..., x(i+m\tau)]$, where m is the embedding dimension, and τ is the time lag. Then, $X(i)$ is arranged in an increasing order of magnitude as

$$X(i) = \left[x(i+(j_1-1)\tau, .., x(i+(j_m-1)\tau\right],$$

where $x(i+(j_1-1)\tau) \le x(i+(j_2-1)\tau) \le ... \le x(i+(j_m-1)\tau)$.

If there exist two elements in $X(i)$ that have the same value, then the elements are ordered as follows: if $j_{i1} < j_{i2}$, then $x(i+(j_{i1}-1)\tau) \le x(i+(j_{i2}-1)\tau)$ is applied. Accordingly, any vector $X(i)$ can be mapped onto a group of symbols as $S(g) = [j_1, j_2, ..., j_m]$, where $g = 1, 2, ..., k$, for $k \le m!$. It is noted that $m!$ is the largest number of distinct symbols and $S(g)$ is one of the $m!$ permutations of m number symbols, which is mapped onto the m number symbols $(j_1, j_2, ..., j_m)$ in m-dimensional embedding space. When each permutation is thought as a symbol, then the vector $X(i)$ is represented by a symbol sequence. Let us define the probability distribution for the distinct symbols P_g such that $\sum_{g=1}^{k} P_g = 1$, where $k \le m!$. Consequently, the computation of PE is formulated as Shannon entropy framework for k different symbols as follows:

$$H_p(m) = -\sum_{g=1}^{k} P_g \ln P_g \tag{1}$$

It is noticed that $H_p(m)$ reaches the maximum value, $\ln(m!)$ in case when $p_i(\pi) = 1/m!$. Thus, the normalized PE can be obtained as

$$PE = \frac{H_p(m)}{\ln(m!)} \tag{2}$$

It is apparent that $0 \le PE \le 1$ and the smaller value of PE, the more regular the time-series. And a larger PE indicates a more random time-series and the upper bound occurs when all permutations have equal probability. If the time-series indicates some kind of ordering dynamics, PE will be smaller than 1. Benefitting from these properties, PE is thought as a suitable measure for quantifying local and dynamic changes of the time-series.

The computation of PE is associated with the selection of the parameters, i.e., the length of the time-series N, embedding dimension m, and lag τ. The embedding dimension m plays a role in the estimation of PE since it is related with the number of available symbols. It is known that the choice of m depends on the length N in a way that $N \ge m!$ to get reliable statistics [11]. As reported in [11], $m = 3$ is chosen in this study. In addition, since τ has a little effect on the estimation of PE, the parameter $\tau = 1$ is used.

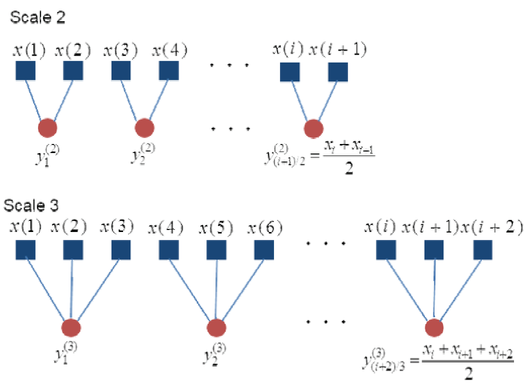


그림 1. 스케일 s = 2와 3에서 coarse-grained 과정의 도식.
Figure 1. Schematic illustration of the coarse-grained process of the time-series for scale factor s = 2 and 3.

2.2 Multiscale PE

MPE has been developed to compute the PE set of time-series over different time scales and is calculated as follows:

1) Consider the time-series $\{x(i): i = 1, 2, \cdots, N\}$, which is divided into several coarse-grained time-series, $\{y_j^{(s)} : j = 1, 2, 3 \cdots \cdots, N/s\}$ as

$$y_j^{(s)} = \frac{1}{s} \sum_{i=(j-1)s+1}^{js} x(i) \tag{3}$$

where s denotes the scale factor and $1 \le j \le N/s$.

2) Compute PE of each coarse-grained time-series $y_j^{(s)}\,(j=1,2,\cdots,N/s)$.

<Figure 1> shows a schematic illustration of the coarse-grained process of the time-series $x(i)$.

However, since the length of $y_j^{(s)}\,(j=1,2,\cdots,N/s)$ is determined by the scale factor s, the variance of MPE become larger as the scale factor s increases.

2.3 Composite Multiscale PE

In order to reduce the possible large variance of MPE at large scale, here, a more accurate MPE, namely, CMPE is presented. The CMPE algorithm is described as follows:

1) Coarse-grained procedure. For a one-dimensional time-series $\{x(i):i=1,2,3\cdots,N\}$, the sampling time-seres are constructed as

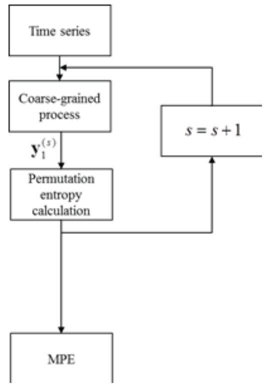
$$Y_{i,j}^{(s)} = x_{i+(j-1)s}, \tag{4}$$

where $i=1,2,\ldots,s$ and $1 \le j \le N/s$.

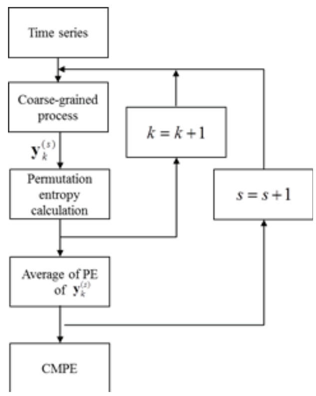
2) Compute CMPE as

$$CMPE(x,s,\tau) = \frac{1}{s}\sum_{i=1}^{s} PE(Y_{i,j}^{(s)}(i,:),\tau). \tag{5}$$

In <Figure 2>, the flowchars of CMPE is shown with comparison with MPE.



(a)



(b)

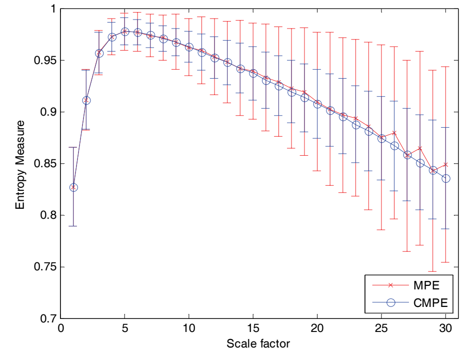
그림 2. MPE와 CMPE의 플로우차트. (a) MPE. (b) CMPE.

Figure 2. Flowcharts of MPE and CMPE. (a) MPE. (b) CMPE.

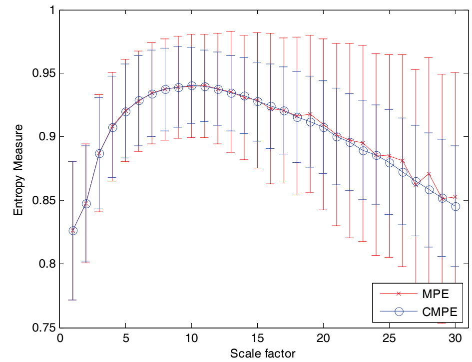
3. Experimental Results

This study used an EEG dataset which is publicly available online for epilepsy research literature [14]. The dataset consists of five subsets (denoted as Z, O, N, F, and S), which each set contains 100 single channel EEG segments of 23.6 s duration. These EEG signals have been selected from continuous multichannel EEG recordings after visual inspection for artifact rejection. The sets Z and O have been obtained from five healthy volunteers with eye open and closed, respectively. The sets N and F have been recorded in seizure-free intervals from five patients in the epileptic zone (set F) and from the hippocampal formation of the opposite hemisphere of the brain (set N), which are referred to as inter-ictal EEG recordings. Finally, the set S have been taken in ictal periods from patients, containing seizure activity. For the type of epilepsy, the patients have partial (focal) seizure which may then have developed to secondary generalized tonic-clonic seizures. The set Z and O have been measured extracranially with standard electrode locations by international 10-20 system, while the sets N, F and S have been recorded from intracranially. For intracranial recordings, depth electrodes were implanted symmetrically in the hippocampal formations and strip electrodes were implanted in the lateral and basal regions of the neocortex. Specifically, the EEG recordings of sets N and F have been taken from the relevant depth electrodes, while those of set S have been obtained from all electrodes (depth and strip). All EEG signals were sampled with   Hz using 12-bit A/D resolution and ranges in the spectral bandwidth from 0.5 to 85 Hz. In addition, the EEG recordings have been recorded 128 channel amplifier setup with an average common reference. In this study, the sets N (normal), Z (interictal), and S (ictal) are chosen to estimate the multiscale entropies. Figures 4(a)-(c) show the representative EEG recordings for normal, interictal and ictal periods, respectively.

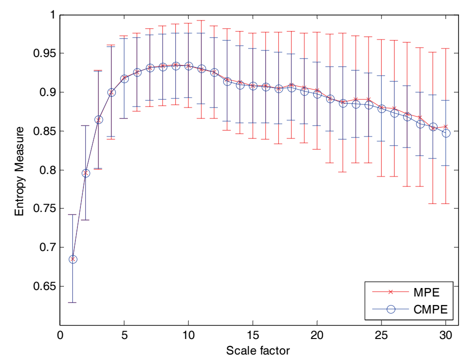
The EEG signals were divided into non-overlapping windows with length of 2 sec. For a each window of EEG recordings, the MPE and CMPE were computed from scale 1 to scale 20.



(a)



(b)

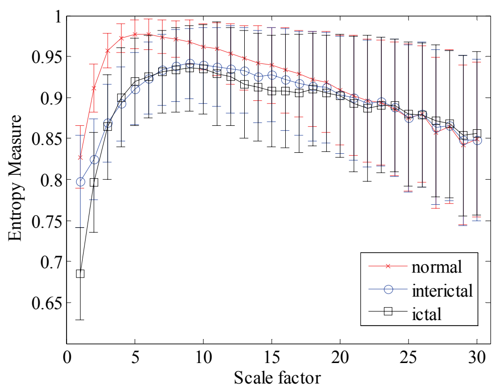


(c)

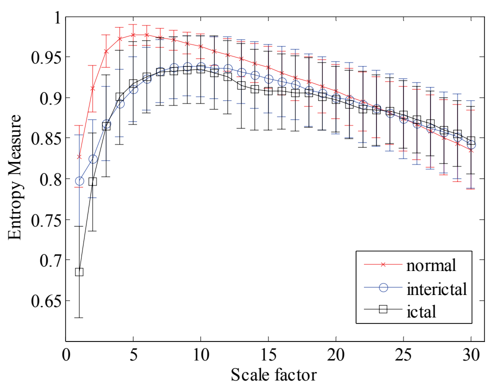
그림 3. 정상, 발작간기, 발작기의 MPE와 CMPE 결과. (a) 정상상태, (b) 발작간기, (c) 발작기.

Figure 3. Results of MPE and CMPE of normal, interictal, and ictal EEG recordings (2 sec window). (a) Normal, (b) Interictal, (c) Ictal.

<Figure 3> depict the entropy estimation results of the MPE and CMPE with 2 sec window for three EEG recordings. As shown in simulation studies, the CMPE reduces the variance of estimated entropy values as compared to MPE, especially at large scales.



(a)



(b)

그림 4. 정상, 발작간기, 발작기 뇌파의 MPE와 CMPE 비교 결과. (a) MPE (2 초), (b) CMPE (2초).

Figure 4. Entropy values of MPE and CMPE of normal, interictal, and ictal EEG recordings. (a) MPE (2 sec window), (b) CMPE (2 sec window).

<Figure 4> show the comparison results of entropy estimation for three different groups, i.e., normal, inter-ictal, and ictal EEG recordings. As can be seen, for both the MPE and CMPE, the mean values of entropies of normal EEG recording are higher than those of other two groups across all scales. Also between inter-ictal and ictal groups, the entropy values of ictal EEG recording indicated lower level than those of inter-ictal one. It is noticeable that there are much decreased overlaps between normal and inter-ictal EEG recordings from scale 2 to scale 12 approximately.

표 1. 정상, 발작간기, 발작기 뇌파를 이용한 PE, MPE, CMPE 분류 정확도 결과

Table 1. Overall classification accuracy of the PE, MPE and CMPE methods for normal, inter-ictal, and ictal EEG recordings.

Methods	1 sec window	2 sec window
PE	79. 2 %	80.1 %
MPE	91.4 %	93.3 %
CMPE	93.1 %	95.2 %

Finally, to assess the classification ability between normal, inter-ictal and ictal EEGs, the MPE and CMPE have been used as features of a support vector machine (SVM) classifier [15, 16]. The entropy values from scale 1 to scale 12 were chosen as features. To validate the classification capability as an online monitoring, the non-overlapping window length of 1 sec and 2 sec were used. Hence, the features of the MPE and CMPE are fed into a SVM classifier for training to obtain the classification model. The SVM method used in this study was SMV type 1, which is known as C-SVM, where the regularization parameter C was set to 100. A radial basis function

(RBF) was chosen as the kernel function of the C-SVM. The kernel parameter of RBF was set to the reciprocal of the number of features. Here, $\gamma = 1/12$ was used. The classification was carried out using all 500 EEG recordings. The EEG recordings was randomly divided as training (70%) and testing (30%) signals, respoectively. Then, the average classification accuracy was obtained over 20 repetitions. <Table 1> shows the overall classification results of the conventional single-scale based PE, MPE and CMPE methods using a RBF-SVM classifier. As seen, compared to other two methods, the CMPE yields the remakably improved classification accuracy of different neurological EEG recordings. In addition, it is apparent that the MPE enables a higher classification accuracy compared to conventional single-scale based PE, implying the usefulness of multiscale entropy measure.

4. Conclusions

This paper has presented a new multiscale based PE which significantly reduces the variance of estimation of entropy in the case of a short time-series, thus is suitable for online monitoring of short EEG recordings. Although the MPE provides entropies over multiple temporal scales, it suffers from a large variance at large scales, implying its unsuitableness for reflecting dynamic characteristics of a short time-series. In case of the neurophysiological signals such as EEG, it is inevitable to estimate an entropy quantity with short data length due to its nonstaionarity nature. By employing a composite average of all coarse-grained time-series, it leads to a credible multiscale based PE, i.e., CMPE. Through the simulation studies using both white and 1/f noises, the CMPE has shown its effectiveness to estimate entropy more accurately, especially at large scales. Experimental results using normal, inter-ictal and ictal EEG recordings have shown that the CMPE measure has rendered an improved discrimination capability for three different neurological states (normal, inter-ictal, and ictal states) than the conventional PE family.

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뇌파를 이용한 뇌전증 발작 검출을 위한 멀티스케일 치환 엔트로피 분석기법

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요 약

뇌전도 (Electroencephalogram, EEG)는 뇌의 전기적 활동도를 평가함으로써 생리학적 상태를 측정하기 위한 표준화된 도구로 이용된다. 뇌전증은 가장 일반

적인 신경 장애 질환으로써 일시적이고 예측불가능한 뇌의 전기적 불안전 상태로 인해 발생하게 된다. 본 논문에서는 짧은 뇌전도의 객관적 수치화를 위해 멀티스케일 치환 엔트로피 기법을 제안한다. 본 제안 기법은 뇌전도의 멀티스케일 특징을 추출하기 위한 coarse-grained 기법을 사용하고 짧은 뇌전도에 적용 가능한 치환 엔트로피를 구하는 과정으로 구성된다. 따라서 제안하는 CMPE 기법은 데이터의 길이에 상관없이 일정한 엔트로피 값을 구할 수 있게 한다. 이러한 점은 CMPE 기법의 뇌파분석에 장점으로 나타난다. 본 제안방법은 뇌전증 뇌파와 정상 뇌파의 차이점을 효과적으로 구분함으로써 뇌전증 발작의 탐지의 효과적임을 보인다.

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