Computation of the Normalized Prediction Error of the Electroencephalogram Signal

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Abstract
In this paper, the normalized prediction error of the electroencephalogram (EEG) signal recorded at five different mental tasks was computed. The results indicate that there exists predictability in the EEG signal beyond the baseline prediction of the mean and the one-step-ahead normalized prediction error of EEG signal vary greatly when different mental tasks are implemented, which implies that the one-step-ahead normalized prediction error can be employed as a feature of EEG signal to distinguish different mental tasks. For different subjects, the one-step-ahead normalized prediction error vary greatly even the EEG signal are recorded from the same electrode under the same mental task, which implies that the subjects' individual differences should be considered adequately when the one-step-ahead normalized prediction error is employed to distinguish different mental tasks.

Keywords: Normalized prediction error, electroencephalogram, mental tasks

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1. Introduction
Electroencephalogram (EEG) overall reflects the brain neuron's electrophysiological activities though electrodes placed on the surface of scalp. When mental tasks are implemented, electrophysiological activities of neurons located at certain brain region vary to some extent, which results in the variation of the EEG. Therefore, analysis on EEG gradually becomes one of the most important approaches to explore the mystery of mental process and meanwhile the main research topic in the field of brain-computer interface (BCI) [1].

It has been proved that the mankind's brain can be considered as a complicated nonlinear dynamics system and the EEG signal is nonstationary, time-varying and nonlinear. With the development of nonlinear dynamics, theories related to nonlinear dynamics, such as the correlation dimension, complexity and lyapunov index, are all employed to analyze the EEG signal [2-4]. Although these methods have the advantage of simplicity, large amount of data is absolutely necessary when these methods are used. Furthermore, since these methods only concern with the static values of the data, the influence of noise is almost unavoidable.

Sugihara and May proposed a nonlinear forecasting method to measure the predictability of a dynamical system [5]. Sauer extended this method and defined a normalized prediction error to evaluate the accuracy of the prediction[6]. In this paper, the normalized prediction error of the EEG signal evoked by five different mental tasks is computed. The results indicate that the normalized prediction error of EEG signal vary greatly when different mental tasks are implemented, which implies that the normalized prediction error can be employed as a feature of EEG signal to distinguish different mental tasks. For different subjects, the normalized prediction error vary greatly even the EEG signal are recorded from the same electrode under the same mental task, which implies that the subjects' individual differences should be considered adequately when the approximate entropy is employed to distinguish different mental tasks.
2. Research Method

2.1. EEG Signal Recording

The EEG signal used in this study is from the EEG center of Colorado State University [7]. Subjects were seated in a sound controlled booth with dim lighting. Six electrode positions, C3, C4, P3, P4, O1 and O2, were recorded using an elastic electrode cap according to the 10-20 system of electrode placement, as illustrated in Figure 1. Besides, other two electrodes were placed above and below the left eye to obtain the electro-oculogram (EOG). The impedance of all of the electrodes is less than 5kΩ. The EEG signal were sampled at 250 samples per second and filtered to 0.1-100 Hz. Signal was recorded for 10 seconds during each mental task and each mental task was repeated five times per session. Most subjects attended two such sessions recorded on separate weeks. The five mental tasks are illustrated as follows.

(i) Baseline: The subjects are asked to open and close their eyes at approximately five second interval. With their eyes closed the subjects are to relax as much as possible.

(ii) Mental Arithmetic: The subjects are given a non-trivial multiplication problem to solve and, as in of the tasks, are instructed not to vocalize or make overt movements while solving the problem. An example of such a task is to multiply the numbers 49 times 78.

(iii) Letter Composing: The Subjects are instructed to mentally compose a letter to a friend or relative without vocalizing.

(iv) Geometric Figure Rotation: The subjects are given 30 seconds to study a drawing of a complex three dimensional block figure after which the drawing is removed and the subject instructed to visualize the object being rotated about an axis.

(v) Visual Counting: The subjects are asked to imagine a blackboard and to visualize numbers being written on the board sequentially, with the previous number being erased before the next number is written.

Figure 1. Illustration of the Position of the Electrode.

2.2. Signal Preprocessing

The EEG signal is susceptible to many artifacts, such as eye-movements, blinks, cardiac signal, muscle noise, etc. It is necessary to eliminate these artifacts or they will do harm to observation and analysis of the EEG signal. The approaches that can be used to eliminate artifacts include regression model, principal component analysis (PCA) and independent component analysis (ICA), etc [8],[9]. ICA is a new method for blind source separation (BSS) developed in mid 90s of the 20th century. In this paper, the FastICA algorithm was employed to eliminate the EEG artifacts[10]. Figure 2(a) illustrates the original EEG signal recorded from C3 electrode of subject 1 under the mental task of Baseline. From the figure we can see that the EEG signal are obviously influenced by the EOG. Figure 2(b) illustrates preprocessing results using the FastICA algorithm. From the figure we can see that the EEG signal was remained and the artifacts were eliminated successfully.
2.3. Normalized Prediction Error

For a time series of \( N \) points \( \{x_i\}_{i=1,2,...,N} \), its \( m \)-dimension phase space is reconstructed as follows [6]:

\[
X_i = (x_i, x_{i+1}, \ldots, x_{i+m-1}) \quad i = 1, 2, \ldots, N - m + 1
\]  

(1)

where \( X_i \) is a vector with \( m \) data points from \( x_i \) to \( x_{i+m-1} \). Obviously, totally \( N-m \)-1 such vectors are obtained.

For one index point \( X_i \) in the embedding space \( X \), \( \{X_j\}_{j=1,2,...,k} \) are its \( k \) nearest neighbors. With a translation horizon of \( H (H \geq 0) \) time steps ahead, the prediction is the average translation given by:

\[
\langle v \rangle = \frac{1}{k} \sum_{j=1}^{k} X_{i+H}
\]  

(2)

The difference between the actual and average translation is the prediction error:

\[
\epsilon_{\text{pred}} = |X_{i+H} - \langle v \rangle|
\]  

(3)

The prediction error for the mean of the time series is:

\[
\epsilon_{\text{mean}} = |X_{i+H} - \langle x \rangle|
\]  

(4)

where \( \langle x \rangle \) indicates the average value of time series \( \{x_i\}_{i=1,2,...,N} \). Then the normalized prediction error (NPE) for a translation horizon of \( H \) is:

\[
\text{NPE}(H) = \frac{RMS(\epsilon_{\text{pred}})}{RMS(\epsilon_{\text{mean}})}
\]  

(5)

where \( \text{RMS} \) indicates root mean square. If the value of NPE(H) is less than 1.0 obviously when \( H \leq H_0 \), it indicates there exists predictability in the time series and \( H_0 \) reflects the degree of the determinism. The larger the value of \( H_0 \) is, the higher the degree of the determinism is.

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The embedding dimension \( m \) and the number of nearest neighbors \( k \) are optimized according to the method described by Schiff and co-workers\[11\]. Firstly, search for the minimum value of NPE as a function of \( m = 1, 2, \ldots, m_{\text{max}} \) with \( k = 1 \). The optimal embedding dimension, \( m_{\text{opt}} \), is set to the value of \( m \) that corresponds to the minimum NPE. Secondly, search for the minimum value of NPE as a function of \( k = 1, 2, \ldots, k_{\text{max}} \) with \( m = m_{\text{opt}} \). Similarly, the optimal number of nearest neighbors \( k_{\text{opt}} \) is set to the value of \( k \) that corresponds to the minimum NPE.

### 3. Computation Results

The EEG signal recorded at five different mental tasks was preprocessed to eliminate the artifacts firstly, and then the NPEs were computed. For the subjects' participation degree varies from trail to trail, the NPEs derived from the same mental task but different trail were averaged. Figure 3 illustrates the average NPEs derived from the EEG signal recorded at five different mental tasks of subject 2. From the figure we can see that the average NPEs of the EEG signal are obviously less than 1.0 when \( H \) is less than 5, which indicates that there exists predictability in the EEG signal beyond the baseline prediction of the mean. In other words, chaos is detected in the EEG signal.

![Figure 3. The average NPEs derived from the EEG signal of subject 2](image)

To investigate the average NPEs under different mental task, the one-step-ahead NPEs (\( H=1 \)) are considered. Figure 4 illustrates the average one-step-ahead NPEs of subject 2. From the figure we can see that, for the EEG signal recorded from the same electrode, the average value of one-step-ahead NPEs is largest under the mental task of Geometric Figure Rotation, followed by Mental Arithmetic, Base line, Visual Counting and Letter Composing. On the other hand, the value of one-step-ahead NPEs is always largest for the EEG signal recorded from electrode O1 and O2. Computation results of the EEG signal of Subject 1 and Subject 5 are similar to that of subject 2.

Figure 5 illustrates the average one-step-ahead NPEs of subject 4. From the figure we can see that, for the EEG signal recorded from the electrode C3, C4, P3 and P4, the average value of one-step-ahead NPE is largest under the mental task of Visual Counting, followed by Mental Arithmetic, Letter Composing Geometric Figure Rotation and Base line. However, for the EEG signal recorded from the electrode O1 and O2, the average value of one-step-ahead NPE is largest under the mental task of Visual Counting, followed by Mental Arithmetic, Base line, Letter Composing and Geometric Figure Rotation. Computation results of the EEG signal of other Subject are similar to that of subject 2 and subject 4.
4. Conclusion

In this paper, the NPEs of EEG signal evoked by five different mental tasks was computed. Mainly two conclusions are drawn. Firstly, the computational results indicate that the average NPEs of the EEG signal are obviously less than 1.0 when H is less than 5, which indicates that there exists predictability in the EEG signal beyond the baseline prediction of the mean. Secondly, the average value of one-step-ahead NPEs of EEG signal varies greatly when different mental tasks are implemented, which implies that the value of approximate entropy can be used to distinguish the mental task that is happening. It is important to note that similar conclusions can be drawn when H is set to other integer, such as 2 and 3.

The computational results also indicate that the average value of one-step-ahead NPEs varies greatly for different subject, even the EEG signal derived from the same electrode and the same mental task are implemented. There are mainly two possible reasons for the variation. Firstly, there exists individual difference between different subjects. Secondly, the subjects’ participation degree in the experiment is different. It should be pointed out that the variation of
NPEs between subjects doesn’t affect applying the one-step-ahead normalized prediction error to distinguish the mental tasks. However, the individual difference of subjects should be considered adequately.

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References