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Estimation of genuine and random synchronization in multivariate neural series

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ABSTRACT

Synchronization is an important mechanism that helps in understanding information processing in a normal or abnormal brain. In this paper, we propose a new method to estimate the genuine and random synchronization indexes in multivariate neural series, denoted as GSI (genuine synchronization index) and RSI (random synchronization index), by means of a correlation matrix analysis and surrogate technique. The performance of the method is evaluated by using a multi-channel neural mass model (MNMM), including the effects of different coupling coefficients, signal to noise ratios (SNRs) and time-window widths on the estimation of the GSI and RSI. Results show that the GSI and the RSI are superior in description of the synchronization in multivariate neural series compared to the S-estimator. Furthermore, the proposed method is applied to analyze a 21-channel scalp electroencephalographic recording of a 35 year-old male who suffers from mesial temporal lobe epilepsy. The GSI and the RSI at different frequency bands during the epileptic seizure are estimated. The present results could be helpful for us to understand the synchronization mechanism of epileptic seizures.

1. Introduction

In neurological studies, synchronization is recognized as a key feature to indicate the information process in a normal or abnormal brain (e.g. Buzsáki, 2004; Buzsáki & Draguhn, 2004; Fell et al., 2001; Varela, Lachaux, Rodriguez, & Martinerie, 2001). The estimated synchronization of the experimental and clinical data, for instance multivariate neural signals, become the signatures of brain pathologies, or brain functions, or the early diagnosis and monitoring of brain disorder. (Aarabi, Wallois, & Grebe, 2008; Carmeli, Knyazeva, Innocenti, & De Feo, 2005; Darvas, Ojemann, & Sorensen, 2009; Knyazeva et al., 2008; Rudrauf et al., 2005; Stam, Jones, Nolte, Breakspear, & Scheltens, 2007). In order to investigate synchronization in the brain, multiple electrodes are often used to record the neural signals in different areas of the brain simultaneously. Therefore, how to estimate the synchronization index of multivariate neural signals has become a crucial issue in neural signal processing.

Some methods have been developed to estimate the synchronization index (or correlation coefficient) between two neural series, for instance cross-correlation, spectrum-based coherence, synchronization likelihood, mutual information, nonlinear interdependence, phase synchronization, correntropy coefficient, event synchronization, and so on (Arnhold, Lehnertz, Grassberger, & Elger, 1999; Brown & Kocarev, 2000; Bruns, 2004; Carter, 1987; Lachaux, Rodriguez, Martinerie, & Varela, 1999; Le Van Quyen et al., 2005; Quian Quiroga, Kraskov, Kreuz, & Grassberger, 2002; Quian Quiroga, Kreuz, & Grassberger, 2002; Stam & van Dijk, 2002; Xu, Bakardjian, Cichocki, & Principe, 2008). To analyze multivariate neural series, we may repetitively use bivariate measure methods to obtain the synchronization index among neural series. However, how to obtain a golden synchronization index in multivariate neural signals is still a bottleneck problem (Allefeld & Kurths, 2004; Pereda, Quian Quiroga, & Bhattacharya, 2005). Recently, an S-estimator has been developed to estimate the synchronization in multi-channel EEG series (Carmeli et al., 2005). In this method, the quantified synchronization is inversely proportional to the embedding dimension of the dynamical system, and is independent of the total power and the time dimension of the neural signals. The disadvantage of the S-estimator is that the estimated synchronization index includes random and/or artifact components, because the synchronization is often estimated over finite-length data, so the estimated synchronization includes, to some extent, random and/or artifact information (Müller, Baier, Rummel, & Schindler, 2008; Plerou et al., 2002). In a recent study, a concept of genuine synchronization was proposed for the first time by

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Müller et al. (2008) to remove the random (and/or artifact) components in multivariate neural signals. In this method, the genuine cross-correlation strength (TCS) was estimated by means of the significant deviation of the eigenvalues (or partial eigenvalues) of the linear zero-lag cross-correlation matrix. However, all of eigenvalues contain rich information (Kwapień, Drożdż, & Oświęcimka, 2006), so this information should be used.

In this paper, we propose a method to estimate the GSI and the RSI in multivariate neural signals. To test the performance of the method, a multi-channel neural mass model (MNMM) (Cui, Li, & Gu, 2009) is applied to generate multivariate neural signals. The effects of different coupling coefficients, signal to noise ratios (SNRs) and time-window widths on the method are investigated. Application of the method to the multivariate long-term EEG recording of a 35 year-old male suffering from mesial temporal lobe epilepsy is demonstrated as well.

2. Methods

2.1. Correlation matrix analysis

Equal-time correlation is a simple method to measure the synchronization between two series. Consider multivariate neuronal data $\mathbf{Z} = \{z_i(n)\}$, $i = 1, \ldots, M$, $n = 1, \ldots, T$, where M is the channel number and n is the number of data points in time window T. To provide the same scale for all the neuronal population activities, the normalized data $\mathbf{X} = \{x_i(n)\}$ are first calculated by $x_i(n) = (z_i(n) - \langle Z_i \rangle)/\sigma_i$, where $\langle Z_i \rangle$ and σ_i are the mean and standard deviation of $z_i(n)$, respectively. Then the equal-time correlation matrix can be constructed as

$$\mathbf{C} = \frac{1}{T} XX', \tag{1}$$

where the superscript denotes transposition. It is noted that we can also select other correlation methods to construct the correlation matrix $\mathbf{C}$, such as phase synchronization, synchronization likelihood, mutual information, nonlinear interdependency and event synchronization. The selection of the method depends on the nature of the data being analyzed.

The eigenvalue decomposition of $\mathbf{C}$ is

$$\mathbf{C}\mathbf{v}_i = \lambda_i \mathbf{v}_i, \tag{2}$$

where eigenvalues $\lambda_1 \le \lambda_2 \le \cdots \le \lambda_M$ are in increasing order and $v_i, i = 1, \ldots, M$ are the corresponding eigenvectors. As $\mathbf{C}$ is a real symmetric matrix, all eigenvalues are real numbers, and the trace of $\mathbf{C}$ is equal to the number of series M. When all the time series are correlated perfectly, the entries of matrix $\mathbf{C}$ are all equal to 1. The maximum eigenvalue is M and the others are zeros. However, in practice, even though all the time series are uncorrelated completely, the computed correlation coefficients are not zeros due to the effect of the length of the data, and they follow a bell-shaped distribution (i.e. they are random correlations or artifact information). More universal properties of random matrices can be found in (Allefeld, Müller, & Kurths, 2007; Müller & Baier, 2005; Plerou et al., 2002; Seba, 2003; Wilcox & Gebbie, 2007).

2.2. Surrogate

When the multivariate time series are derived from an independent linear stochastic process, the ideal correlations between time series are zeros. Unfortunately, due to the effect of the algorithm and the length of the data, the calculated correlations exhibit a little bias, and are not purely zero. In this paper, a surrogate method is used to reduce the 'bias' (i.e. random correlations or artifact information) in practical time series. The surrogate method proposed by Andrzejak, Kraskov, Stögbauer, Mormann, and Kreuz (2003) is employed, which iteratively permutes the original sample values of each series. Details can be found in the Appendix. The randomized multivariate data have the same size (channel number M and the number of data points n in time window T) and in particular the same power spectrum of each time series as its original time series. Based on the surrogate series, the equal-time surrogate correlation matrix $\mathbf{R}$ can be calculated: $\lambda_1^s \le \lambda_2^s \le \cdots \le \lambda_M^s$ are denoted as the eigenvalues of surrogate matrix $\mathbf{R}$. The distribution of the surrogate eigenvalues λ_i^s can reflect the random synchronization of the multivariate time series.

2.3. GSI and RSI estimator

The S-estimator has been proposed to assess synchronization in multivariate EEG series by means of the distributions of the eigenvalues of the covariance matrix (Carmeli et al., 2005). The normalized eigenvalues $\lambda_i^{(1)}$ of the covariance matrix are defined as follows:

$$\lambda_i^{(1)} = \frac{\lambda_i}{\sum_{i=1}^{M} \lambda_i}, \quad i = 1, \ldots, M. \tag{3}$$

For a random multivariate time series, the minimum and maximum eigenvalues of the random correlation matrix are $\lambda_{\min,\max} = 1 + \frac{1}{Q} \pm 2\sqrt{\frac{1}{Q}}$, $Q = T/M$. That is to say, although all the multivariate time series are not correlated, the eigenvalues range in the bound $[\lambda_{\min}, \lambda_{\max}]$ (Plerou et al., 2002; Seba, 2003). The calculated S-estimator is a non-zero value for random multiviate time series (Müller et al., 2008; Plerou et al., 2002). The S-estimator (total synchronization) is composed of genuine and random synchronizations. To reduce the effects of the random components in the total synchronization, the eigenvalues are divided by the averaged surrogate eigenvalues; that is,

$$\lambda_i^{(2)} = \frac{\lambda_i/\bar{\lambda}_i^s}{\sum_{i=1}^{M} \lambda_i/\bar{\lambda}_i^s}, \quad i = 1, \ldots, M, \tag{4}$$

where $\bar{\lambda}_i^s$ is the average eigenvalues of the surrogate series over the SN realizations.

In a similar manner, the normalized surrogate eigenvalues are obtained as follows:

$$\lambda_i^{(3)} = \frac{\bar{\lambda}_i^s}{\sum_{i=1}^{M} \bar{\lambda}_i^s}, \quad i = 1, \ldots, M. \tag{5}$$

All the synchronization indexes can be summarized as follows:

$$SI^{(k)} = 1 + \frac{\sum_{i=1}^{M} \lambda_i^{(k)} \log\left(\lambda_i^{(k)}\right)}{\log(M)}, \quad k = 1, 2, 3. \tag{6}$$

When $k = 1$ (Eq. (3)), this is an S-estimator, which is a measure of the total amount of synchronization (Carmeli et al., 2005); when $k = 2$ (Eq. (4)), the eigenvalues of $\lambda_i^{(2)}$ are applied, and the genuine synchronization index (GSI) is obtained. To understand how this measure works, two cases should be considered. If genuine correlation does not exist, the normalized eigenvalues $\lambda_i^{(2)}$ are all equal to $1/M$, so $SI^{(2)} = 0$; on the other hand, if all the time series are correlated perfectly, the largest eigenvalue $\lambda_M = M$, and the others are equal to zero, i.e. the largest normalized eigenvalue is $\lambda_M^{(2)} = 1$, and the others are zero, so $SI^{(2)} = 1$. The random synchronization index (RSI) can be obtained when $k = 3$ (Eq. (5)).