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Detecting spatiotemporal nonlinear dynamics in resting state of human brain based on fMRI datasets

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ABSTRACT

In this work, a nonlinear dynamics method, coupled map lattices, was applied to functional magnetic resonance imaging (fMRI) datasets to examine the spatiotemporal properties of resting state blood oxygen level-dependent (BOLD) fluctuations. Spatiotemporal Lyapunov Exponent (SPLE) was calculated to study the deterministic nonlinearity in resting state human brain of nine subjects based on fMRI datasets. The results show that there is nonlinearity and determinism in resting state human brain. Furthermore, the results demonstrate that there is a spatiotemporal chaos phenomenon in resting state brain, and suggest that fluctuations of fMRI data in resting state brain cannot be fully attributed to nuclear magnetic resonance noise. At the same time, the spatiotemporal chaos phenomenon suggests that the correlation between voxels varies with time and there is a dynamic functional connection or network in resting state human brain.

1. Introduction

Functional magnetic resonance imaging (fMRI) has emerged as a useful and noninvasive technique for studying the function of the brain. Using magnetic resonance technique, researchers have found that it is possible to indirectly detect changes in blood-oxygenation levels that are a result of neuronal activation. In the past decade, fMRI has provided a powerful approach to study the structure-function relationship in the human brain. Most of studies concentrated on detecting or estimating brain regions involved in specific cognitive or sensor-motor tasks.

Conscious rest has been widely used as a baseline condition in positron emission tomography (PET) and fMRI neuroimaging experiments. In most cases, rest state is defined as a state that differs from the active state both in terms of conditions (open/closed eyes, absence/presence of a stimulus input) and instructions given to the subject. A rest state can therefore be used in a wide variety of experiments. However, it is an ill-defined mental state because it may vary both from one subject to another and within the same subject [1].

The complex behavior of the hemodynamic response is a global phenomenon and the reconstruction of the dynamics recorded in fMRI data should make use of the vast amount of spatial information acquired [2]. Electroencephalography (EEG) and magneto-encephalography (MEG) analysis can achieve higher accuracy (performance) by combining spatial and temporal approaches [3,4]. Compared with EEG of low spatial resolution, fMRI datasets offer millimeter spatial resolution with temporal resolutions of the order of seconds. It can offer more spatial information than EEG/MEG. Hence, spatiotemporal analysis is an important analytic tool of fMRI datasets in brain research [5].

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As a linear spatiotemporal analysis method, correlation analysis has been widely used in the study of functional connectivity based on fMRI datasets. It assumes that the relevant information about the interactions of brain regions is reflected by a linear relationship between the values of two signals at the same time [6,7]. However, this hypothesis has not thoroughly been investigated. Recent studies indicated the nonlinear nature of BOLD response [8]. Many nonlinear models between stimulation and fMRI response are established [9,10]. These nonlinearities are believed to be caused by viscoelastic properties of blood vessels [8,11], and nonlinearities at the neuronal level, such as the adaptive behavior of neuronal activity [12–16]. The BOLD response is more sensitive to subtleties of neuronal activity than previously suggested in the literature [17].

Even though there has been an effort to study nonlinear dynamics of brain using Electroencephalogram (EEG) [4,18–20], very little work has been done in applying method of nonlinear dynamics to fMRI, particularly during the resting state. Fractional Gaussian noise property of fMRI datasets is analyzed using Hurst exponent [21]. An extension of the delta-epsilon approach is applied to fMRI data to evaluate whether a time course of a candidate pixel provides additional information concerning the time evolution of reference pixel time series [22]. The nonlinearity arising from the finite dimensional dynamics is then characterized using patterns of singularities in the complex plane. A finite embedding dimension is a measure of the determinism of the system, which can be quantified using information theoretic measures like Lempel-Ziv complexity [23]. Using spatial embedding of fMRI datasets, local spatiotemporal chaos in baseline [24] has been reported, but the significance of nonlinearity has not been tested on fMRI datasets by using surrogate data. Though the nonlinearity analysis of fMRI dataset in human brain has attracted many researchers, most of works on nonlinear analysis of fMRI are carried on single time series voxel by voxel, as is traditionally done in the nonlinear signal processing literature. In addition, because of no significant stimulation in resting state human brain, it is difficult to detect the nonlinearity by the relationship between stimulation and its fMRI response.

In this work, a nonlinear dynamics method, coupled map lattices (CML), was applied to fMRI datasets of resting state human brain. The Spatiotemporal Lyapunov Exponent (SPLE) was calculated for fMRI datasets and the nonlinearity of fMRI datasets was tested by using surrogate data generated from the fMRI datasets. The positive SPLE was confirmed by a finite embedding dimension which is a measure of the determinism of fMRI datasets in resting state brain. The results demonstrate that there is a spatiotemporal chaos phenomenon in resting state brain, and suggest that the fluctuations in resting state brain cannot be fully taken as nuclear magnetic resonance (NMR) noise, but can be the spatiotemporal properties inhered in resting state brain. At the same time, the deterministic nonlinear dynamics can get an estimation of spatiotemporal correlation of resting state brain, and the correlation between voxels varies with time and there is a dynamic functional connection or network in resting state brain.

2. Method

Lyapunov exponents can measure the divergence (or convergence) of nearby trajectories. Although there have been a number of algorithms which attempt to estimate the underlying dynamics recently, most of these algorithms are not suitable for a spatiotemporal dataset such as fMRI but can only be applied to single time series.

2.1. Spatiotemporal Lyapunov Exponent

Ricard V. SolÉ and Jordi Bascompte presented a method [25] to evaluate the SPLE numerically when very short time series are obtained from a spatially distributed dynamical system. This method bases on the concept of coupled map lattices. Coupled map lattices have been widely used as models of spatiotemporal chaos in physics, chemistry and biology.

A dynamical system is given by a set of nonlinear equations as follows:

$$x^j_{n+1}(\mathbf{k}) = F^j_\mu(\mathbf{x}_n(\mathbf{k})) + C^j_\gamma(\mathbf{x}_n(\mathbf{k})), \tag{1}$$

where $\mathbf{j} = \mathbf{1}, \dots, \mathbf{s}, \mathbf{x} = (x^1_n, \dots, x^s_n)$ and $F^j_\mu(\mathbf{x}), C^j_\gamma(\mathbf{x}) \in C^2(U)$. U is a compact set and $U \subset \mathbf{R}^s$. This set of maps is then defined on a two-dimensional lattice

$$\Lambda^2(L) = \{\mathbf{k} = (\alpha, \beta) | 1 \leqslant \alpha, \beta \leqslant L\}. \tag{2}$$

If we have a time series defined as the set:

$$\Gamma^j(\mathbf{k}) = \{x^j_1(\mathbf{k}), \dots, x^j_m(\mathbf{k})\} \quad \forall \mathbf{k} \in \Lambda^2(L). \tag{3}$$

Using the lagging method, a phase space of new d-dimensional sets can be reconstructed as follows:

$$\Gamma^j_d(\mathbf{k}) = \{X^j_i(\mathbf{k}) = (x^j_i(\mathbf{k}), \dots, x^j_{i+d-1}(\mathbf{k}))\}, \tag{4}$$

where $i = 1, \dots, m - d + 1$ and d is an embedding dimension. Now we consider the global set defined as the union of all local orbits:

$$\Gamma_d(\Lambda) = \bigcup_{k \in \Lambda(L)} \Gamma^j_d(\mathbf{k}) \tag{5}$$

This set is then constructed by $(m\text{-}\ (d\text{-}1))L^2$-points.