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ORIGINAL ARTICLE

The research of constructing dynamic cognition model based on brain network

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Abstract Estimating the functional interactions and connections between brain regions to corresponding process in cognitive, behavioral and psychiatric domains is a central pursuit for understanding the human connectome. Few studies have examined the effects of dynamic evolution on cognitive processing and brain activation using brain network model in scalp electroencephalography (EEG) data. Aim of this study was to investigate the brain functional connectivity and construct dynamic programing model from EEG data and to evaluate a possible correlation between topological characteristics of the brain connectivity and cognitive evolution processing. Here, functional connectivity between brain regions is defined as the statistical dependence between EEG signals in different brain areas and is typically determined by calculating the relationship between regional time series using wavelet coherence. We present an accelerated dynamic programing algorithm to construct dynamic cognitive model that we found that spatially distributed regions coherence connection difference, the topologic characteristics with which they can transfer information, producing temporary network states. Our findings suggest that brain dynamics give rise to variations in complex network properties over time after variation audio stimulation, dynamic programing model gives the dynamic evolution processing at different time and frequency. In this paper, by applying a new construct approach to understand whole brain network dynamics, firstly, brain network is constructed by wavelet coherence, secondly, different time active brain regions are selected by network topological characteristics and minimum spanning tree. Finally, dynamic evolution model is constructed to understand cognitive process by dynamic programing algorithm, this model is applied to the auditory experiment, results showed that, quantitatively, more correlation was

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observed after variation audio stimulation, the EEG function connection dynamic evolution model on cognitive processing is feasible with wavelet coherence EEG recording.

1. Introduction

Brain functional connectivity has played a variety of roles in the study of human cognition and behavior over the past four decades. Functional connectivity has revealed the reorganization of brain networks during cognitive tasks (Sporns, 2011). Thus, in this paper, dynamic evolution model is constructed to understand cognitive process by dynamic programing algorithm based on brain network. Initially, computed tomography (CT) and then magnetic resonance imaging (MRI) were used to probe the large-scale organization of the brain which is estimated by correlation of BOLD activity, identifies coherent brain activity in distributed and reproducible networks (Vincent et al., 2006). More recently, a variety of imaging modalities—including structural and functional MRI and positron emission tomography (PET) studies have shown characteristic changes in the brains, but thus far has been limited in its capacity to study their temporal evolution. Therefore, the purpose of this paper is to present a data-driven dynamic construction of the state space for the one-pass dynamic programing algorithm so that only the actually active hypotheses are explicitly generated during the process of cognition.

A fair amount of investigation has been directed at linking spiking activity to the fMRI blood oxygenation level-dependent (BOLD) response (Nagai et al., 2004), but far less research has sought to relate spiking activity and EEG. The EEG is thought to reflect the postsynaptic potentials in the apical dendrites of pyramidal cells resulting from their mutual alignment, which allows summation of electric fields (Kopal and Burian, 2014). The strength of the signal is related to both the magnitude of the postsynaptic activity and its coherence: postsynaptic currents with low spatiotemporal coherence tend to destructively interfere at the level of the scalp (Lachaux et al., 2002; Onnela et al., 2005). The common synaptic activity that drives variability in the EEG signal likely also generates spike count correlation across neurons. Their cortical generator was calculated using wavelet coherence for each group. Coherence analysis has been extensively applied to the study of neural activity. To overcome the problems due to non-stationary raised in the previous section, it has recently been proposed to apply wavelet analysis for the estimation of coherence among non-stationary signals (Milligen et al., 1995; Santoso et al., 1997). In contrast to Fourier analysis, wavelet analysis has been devised to analyze signals with rapidly changing spectra (Torrence and Compo, 1998). It performs what is called a time–frequency analysis of the signal, which means the estimation of the spectral characteristics of the signal as a function of time. In some sense, wavelet analysis is close to the windowed short-term Fourier transform, especially when using the Morlet wavelet (Osofsky, 2000), but the major difference is that the size of the window is fixed for the short-term Fourier, and it is adapted to the frequency of the signal in wavelet analysis. Because of this difference, wavelet analysis has a more accurate time–frequency resolution (Lachaux et al., 2000; Bonato et al., 1996). However, the utility of wavelet analysis is that it provides not only the time-varying power-spectrum, but also the phase spectrum, which is needed to compute the coherence. This makes wavelet analysis a natural choice for the estimation of coherence between non-stationary signals (Lachaux et al., 1999).

Functional networks have largely been identified in task-based data by graph theory methods, where synchronized activity across different regions is thought to reflect intrinsic connectivity (Shafto and Tyler, 2014). Networks are formed from the wavelet coherence of multiple head electrode points and are thought to be functionally specialized by virtue of their interregional connectivity. Much of our understanding of brain connectivity rests on the way that it is measured and modeled. We consider a functional connective model approach: it has its basis in graph theory that aims to describe the network topology of (undirected) connections of the sort measured by noninvasive functional connectivity between remote sites. After brain network is constructed based on wavelet coherence, different time stages are divided during the stimuli process, the module is got by minimum spanning tree in every stage, and these are applied in dynamic programing in different states to construct the dynamic evolution model. The aim of the present study was to evaluate a possible correlation between the brain connectivity architecture and dynamic evolution processing as extracted from EEG recordings by dynamic model. EEG recording in the brain functional connectivity via wavelet coherence can be technically challenging. We aimed to assess the feasibility and the efficacy of auditory stimuli EEG (Lachaux et al., 2002).

2. Brain network construct and analysis

We discuss the cross wavelet transform and wavelet coherence for examining relationships in time–frequency space between two time series, brain network is constructed and analyzed based the wavelet coherence and graph theory, and minimum spanning tree method is used to module the brain regions, prepared to construct the dynamic model by dynamic programing algorithm.

Functional connectivity between brain regions is defined as the statistical dependence between neurophysiological signals in different brain areas and is typically determined by calculating the relationship between regional times series using wavelet coherence, The nodes of the network are EEG channels, and the edges of the network are weighed by the wavelet coherence values, a weighted graph is a mathematical representation of a set of elements (vertices) that may be linked through connections of variable weights (edges). In the present study, weighted and undirected networks were built. The vertices of the networks are the estimated cortical sources in the EEG, and the edges are weighted by the wavelet coherence within each pair of vertices. The undirected networks are constructed based on the threshold by the weighted Clustering coefficient C