Measuring dynamic process of working memory training with functional brain networks

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ABSTRACT

In this paper, we proposed the functional brain networks and graphic theory method to measure the effect of working memory training on the neural activities. 12 subjects were recruited in this study, and they did the same working memory task before they had been trained and after training. We architected functional brain networks based on EEG coherence and calculated properties of brain networks to measure the neural co-activities and the working memory level of subjects. As the result, the internal connections in frontal region decreased after working memory training, but the connection between frontal region and top region increased. And the more small-world feature was observed after training. The features observed above were in alpha (8-13 Hz) and beta (13-30 Hz) bands. The functional brain networks based on EEG coherence proposed in this paper can be used as the indicator of working memory level.

Keywords

Working memory training, functional brain networks, EEG coherence

1. INTRODUCTION

The research of effect of working memory training on functional brain network was conducted in the paper based on EEG coherence. Working memory, the ability to actively sustain attention to a mental representation, is an essential cognitive brain function that underlies many uniquely human cognitive abilities such as language comprehension, reasoning, and planning. Performance on working memory tasks is affected by a variety of conditions that affect frontal lobe function [1]. It has been shown to be crucial for daily life skills. So the effect of training on working memory ability is worth studying and the functional brain network is a simple method to analysis the connection inside and between main cortical regions

In recent years, many functional brain network methods are proposed in analysis of the signal(s) recorded by electroencephalograph (EEG). Although analysis of structural networks helps us to understand the fundamental architecture of inter-regional connections, we must also consider functional networks directly to elucidate how this architecture supports neurophysiological dynamics. Most of studies based on functional brain networks come from the psychological literature, focusing mainly on the domains of cognitive tasks, mental disorders and different mental states, and few researches were conducted using functional brain networks to detect the human working memory level. In this study, we are interested in the functional network organization underlying working memory performance. The involvement of fronto-parietal regions in WM tasks was shown with different neuroimaging methods such as the intracranial electroencephalography [2].

The paper presents the effect of working memory training on brain networks of subjects, both in structure of the graphic and in complex network properties. The paper has been organized as follows:

Section 2 describes the method of the study, which contained that experiment design, data collection, data preprocessing and mathematics in functional brain networks. In section 3, the result of the experiments and the feature extracted from EEG data. After the description of the result, the discussion of that along with conclusion is described in section 4.

2. Method

2.1 Training and Experiment Design

There are 12 healthy subjects (8 males and 4 females; aged 22.1$\pm$1.5) without history of drug abuse, were recruited in this experiment. The experiment conducted in two stages, which contain 3 series of experiments respectively. There are 6 trials in each series. Every subject did a working memory task in each trial. In first stage, subjects were at the primary level in this task. The second stage was conducted after they were trained to do the same task for a week. Subjects rested for 1 minute between two trails and for 10 minutes between two series. All subjects do the same tasks at least 20 times every day in training stage. The task is that the subjects should remember the balls showed in random position on monitor in a sequence, and clicked the balls in the same sequence in which they showed up.

2.2 EEG Data and Preprocessing

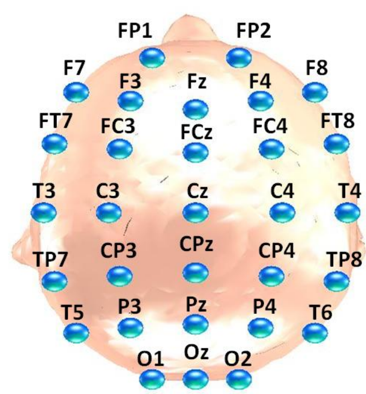

Figure 1. Electrode locations.

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The EEG signals were collected during subjects were doing the working memory tasks by a headset named as Neuroscan and were amplified by NuAmps. 30 electrodes (Ag/AgCl) were attached to the scalp according to the International 10-20 system. The EEG data were recorded from the electrodes (FP1, FP2, F7, F3, FZ, F4, F8, FT7, FC3, FCZ, FC4, FT8, T3, C3, CZ, C4, T4, TP7, CP3, CPZ, CP4, TP8, T5, P3, PZ, P4, T6, O1, OZ and O2 see in Figure 1). The reference electrodes were linked the mastoid behind ears. The EEG data were preprocessed using SCAN 4.3, which contained three stages. Firstly, the ocular artifacts in EEG data were corrected based on reference EOG signals. Secondly the EEG data were done baseline correction and the blocks in which the magnitude of EEG was not in range -150~150 μV were cut off. Thirdly, the EEG data was processed using a band pass filter with cut-off frequencies of 0.5 Hz and 30 Hz and was down sampled from 1000 Hz to128 Hz .

2.3 Coherence and Functional Brain Networks

A network is a mathematical representation of a real-world complex system and is defined by a collection of nodes and links between pairs of nodes. The functional brain network based on EEG represents the synchronization of neural activity among various brain regions. The nodes in functional brain networks are electrodes on the scalp, and the links are synchronization between signals. There are many methods to calculate synchronization in current study, such as correlate, coherence, phase synchronization, granger causality, likelihood synchronization etc [3]. We apply coherence method to measure the synchronization between channels in this paper.

According to Thatcher et al [4], the EEG reflects concerted activity of large scale cell assemblies and thus should be well suited to detect global states of integrated cortical function and to

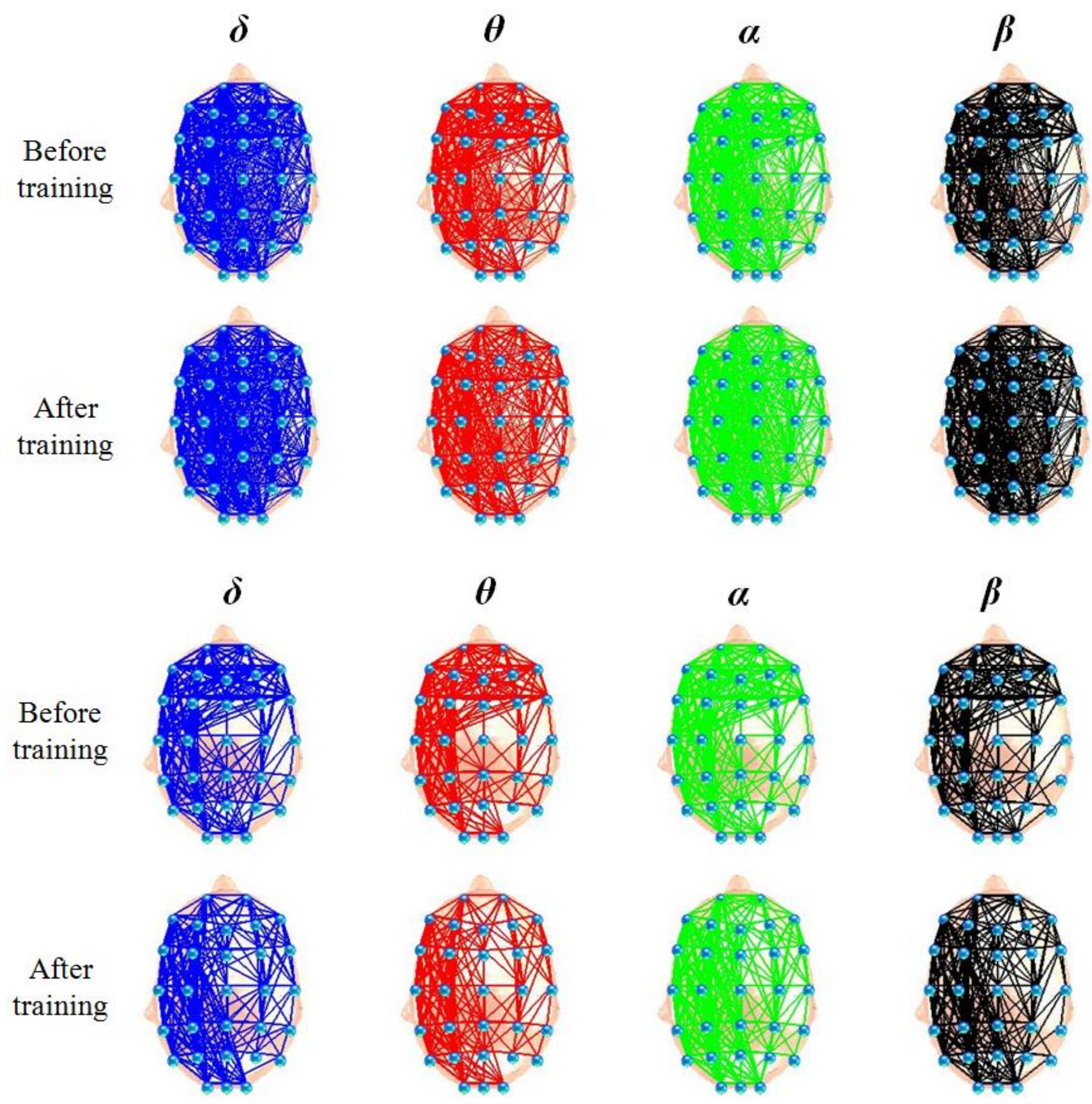

Figure 2. Functional brain networks in different frequency bands when the threshold is 0.3 and 0.4.

elucidate the degree of 'electric coupling' between 'cooperating' neuronal systems. EEG coherence analysis has been developed as a statistical measure for the functional cooperation between two cortical areas. Many studies report the successful use of EEG coherence to measure functional connectivity. The term coherence is a measure for linear frequency dependent entities. A coherence value can range from 0 (no linear relation between the two signals in frequency domain) to 1 (perfect linear synchronization between the two signals at the frequency under consideration).

2.4 Graphic Theory Analysis

The functional brain networks are composed of nodes and edges, and are too complex to extract feature. In order to depict the topological structure, there are many properties measuring the functional brain networks. Especially clustering coefficient, average shortest path length are the most popular and fundamental methods [5, 6] and there are also the principle properties of small-world [7, 8].

3. RESULT

3.1 Feature Extract

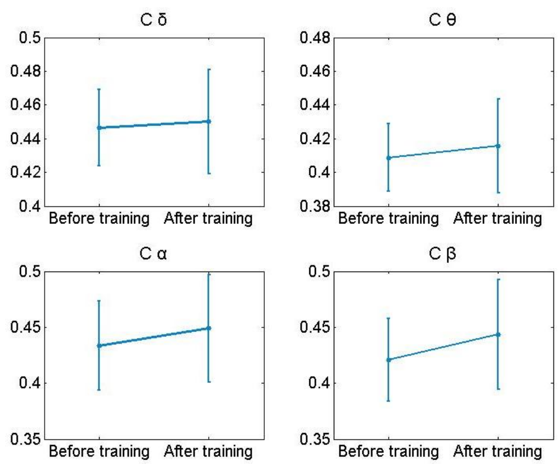

Figure 3. Clustering coefficient of different frequency bands change after training.

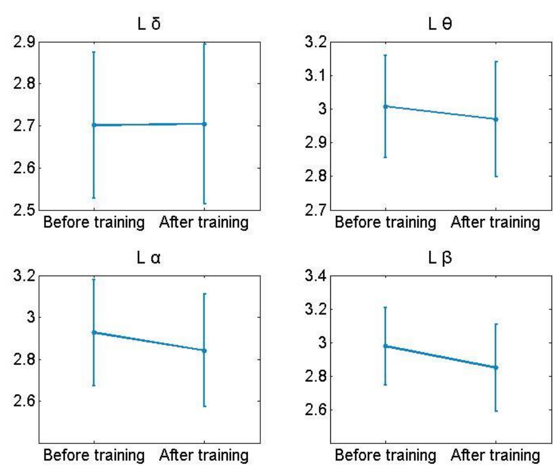

Figure 4. Average shortest path length of different frequency bands change after training.

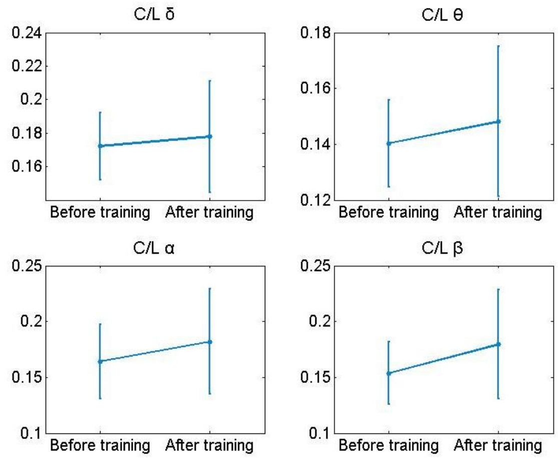

Figure 5. The ratios C/L of different frequency bands change after training.

The functional brain networks in different rhythm were drawn in Figure 2. The different color lines in the brain networks stand for different frequency bands (δ delta: 0.5-4 Hz, θ theta: 4-8 Hz, α alpha: 8-13 Hz, β beta: 13-30 Hz). The width of the line represents the weight of the pair of electrodes. The lines, whose weight is lower than a threshold, were removed. When the threshold was set to 0.3, the brain networks of after training in alpha band and beta band were denser than those of before training. When the threshold was set to 0.4, the connections of before training in frontal region were denser than that of after region but less connection between frontal and top regions. The more connections were in the left hemisphere of brain. But the graph was not more obvious than indicators, because the brain networks were too complex to study. We applied graphic theory method to analysis the topological characters of the functional brain networks.

3.2 Graphic Theory Properties

We can see in Figure 3 the clustering coefficients in theta, alpha, beta bands after training were higher than those before training, which meant the functional brain networks after training had more big community of electrodes than those of drivers when they had not been trained. And in Figure 4 the average shortest path length in theta, alpha, beta bands after training were shorter than those before training, which means the functional brain networks after training were more integrate than those of drivers when they had not been trained.

3.3 Small-World

A small world network is a type of mathematical graph in which most nodes are not neighbors of one another, but most nodes can be reached from every other by a small number of hops or steps. The small-world network has higher clustering coefficient and shorter average shortest path length than random networks. Small-world characteristic is defined by the clustering coefficient (C) and average shortest path length (L), C/L ratio. The C/L ratio in all the four frequency bands was increased significantly after training (see in Figure 5), especially in theta, alpha, beta bands.

3.4 Dynamic brain networks

The ratio C/L changes with trails (See in the Figure 6). The first 18 trials were conducted before subjects had not been trained.

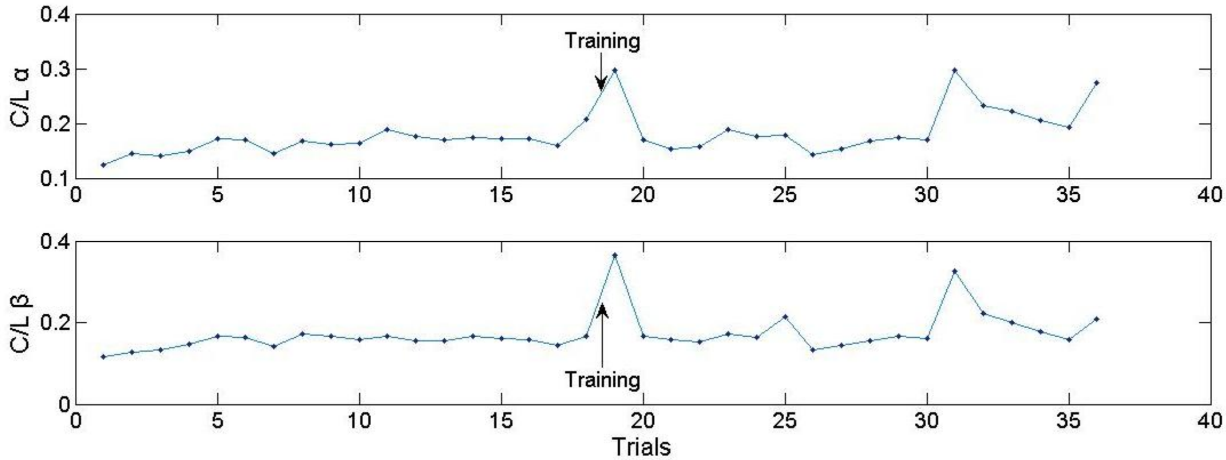

Figure 6. The ratio C/L of functional brain networks changes with trials.

And the last 18 trials were conducted after subjects had been trained. In alpha and beta bands, the ratio C/L increased slowly with trials. Especially after subjects had been trained, the extreme values of ratio C/L were obtained in 19th, 25th and 31st trial.

4. DISCUSSION

Functional brain network is a popular method in the research of neural activity. It can reveal the functional connection among brain regions, and dig more hidden information. Because a set of *N*-channel EEG signal can provide pairs of channels. It also can be used to determine the distribution of community, observe the information flow. But functional brain network is too complex to extract feature directly, because it has more information and its graph is complex and disorder. The most popular method to analysis the topologic structure is graphic theory. In graphic theory analysis, the clustering coefficient and average shortest path length were computed for the indicators to detect the fatigue of drivers. The result described in section 3 manifested that the connections of functional brain networks of trained subjects were more strength than that before they had not been trained. The threshold 0.3 was too low to remove enough edges, so that, the brain network were too dense to observe. Then we set the threshold to 0.4 to remove more edges, so that, the detail features could be observed directly (see in Figure 2)

5. CONCLUDE

The result shown that the internal connections in frontal region decreased after working memory training but the connection between frontal region and top region increased. And the more small-world feature was observed after training. The features observed above were in alpha and beta bands, and can be used to measure the working memory level.

6. ACKNOWLEDGMENTS

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