Alterations in Resting-State after Motor Imagery Training: A Pilot Investigation with Eigenvector Centrality Mapping

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Abstract. Motor training, including motor execution and motor imagery training, has been indicated to be effective in mental disorders rehabilitation and motor skill learning. In related neuroimaging studies, resting-state has been employed as a new perspective besides task-state to examine the neural mechanism of motor execution training. However, motor imagery training, as another part of motor training, has been few investigated. To address this issue, eigenvector centrality mapping (ECM) was applied to explore resting-state before and after motor imagery training. ECM could assess the computational measurement of eigenvector centrality for capturing intrinsic neural architecture on a voxel-wise level without any prior assumptions. Our results revealed that the significant increases of eigenvector centrality were in the precuneus and medial frontal gyrus (MFG) for the experimental group but not for the control group. These alterations may be associated with the sensorimotor information integration and inner state modulation of motor imagery training.

Keywords: Motor imagery, functional magnetic resonance imaging (fMRI), ECM, precuneus, medial frontal gyrus (MFG).

1 Introduction

Motor training, including motor execution and motor imagery training, has been indicated to be effective in mental disorders rehabilitation and motor skill learning [1, 2]. Additional to the improvement of movement in spatial and temporal accuracy, motor training is also accompanied with alterations in human brain's activity. In the last

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decade, the neural mechanism underlying motor training has attracted increasing attention in the neuroimaging explorations. Researchers have conducted extensive investigations on both motor execution and imagery in task state, and have indicated that motor execution and imagery may induce different alterations within brain in spite of their similar neural substrates [3-5]. Recently, many researchers have suggested that resting state may contain rich information on the neural mechanism of motor training and may offer the possibility of more complete detection of specific neural system [6, 7].

Identifying the neural alterations induced by motor training from the resting state aspect has been the focus of many neuroimaging studies in recent years. Xiong et al. (2009) revealed that 4 weeks finger sequential training could induce a significant increase of rCBF (regional cerebral blood flow) in M1 [6]. Albert et al. (2009) found that the fronto-paritial resting state network and the cerebellar resting state network were altered by a visuomotor tracking task [8]. Ma et al. (2011) found dynamic changes (increase-first-then-decreased) in resting state functional connectivity in the rPCG and rSMG during a 4 weeks finger sequential training [7]. Taubert et al. (2011) suggested that learning a challenging motor task could lead to long-lasting changes in resting state network, and the changes occurred in SMA and prefrontal were directly correlated with structural grey matter changes [9]. All these studies on the resting human brain have been focused on motor execution training. However, motor imagery training, as another part of motor training, has been few investigated.

In this study, using functional magnetic resonance imaging (fMRI), we applied a novel graph-based network analysis technique named eigenvector centrality mapping (ECM) to explore the influence of motor imagery training on resting state across the whole brain. ECM has been indicated to be a data-driven method without any prior assumptions, and it could assess the computational measurement of eigenvector centrality for capturing intrinsic neural architecture on a voxel-wise level [10]. We hypothesized that motor imagery training could alter the eigenvector centrality of resting state.

2 Materials and Methods

2.1 Subjects

Fourteen right hand-dominant subjects (seven males, mean age: 22±2 years) participated in the training, and another twelve right hand-dominant subjects (five males, mean age: 24±2 years) were recruited as a control group. Participants with histories of neurological disorders, psychiatric disorders, experience with typewriters, or any experience learning to play musical instruments were excluded. All participants provided written consent according to the guidelines set by the MRI Center of Beijing Normal University.

2.2 Experiment Procedure

The experiment procedure included a pre- resting-state session, two pre-task sessions, a motor imagery training period (experimental group)/a no-training period (control group), a post- resting-state session and two post-task sessions. Here, only the resting-state data was examined. In each 10-min resting-state session, subjects were instructed to keep their eyes closed, relax their mind, and remain motionless as much as possible. In the training period, all participants were instructed that from their index to little finger, each of the four fingers of their right hand represented a single digit number: one, two, three, and four. Fourteen motor imagery practice sessions were employed over 14 consecutive days to make sure the sufficient training. Each training session consisted of two 15-min sections, metronome-pacing and self-pacing respectively. In each section, participants were instructed to imagine tapping sequence 4–2–3–1–3–4–2 with their right hand fingers repeatedly as fast as the pace of the metronome or the pace controlled by themselves for 30 seconds with an interval of 30-s rest. The training period were only performed in the experimental group while participants did not attend any training during the 14 days in the control group.

2.3 fMRI Data Acquisition

Brain scans were performed at the MRI Center of Beijing Normal University using a 3.0-T Siemens whole-body MRI scanner. A single-shot T2*-weighted gradient-echo, EPI sequence was used for the functional imaging acquisition, with the parameters: TR/TE/flip angle = 3000ms/ 40ms/ 90°, the acquisition matrix was 64×64, the field of view (FOV) was 240 mm and slice thickness =5mm with no inter-slice gap. 32 axial slices parallel to the AC-PC line were obtained in an interleaved order to cover the whole cerebrum and cerebellum.

2.4 Image Preprocessing and Analyses

The functional images of both groups were first realigned, spatially normalized into standard stereotaxic space (EPI template provided by the Montreal Neurologic Institute, MNI), re-sliced to 3×3×4mm voxels and smoothed with a 8×8×8 full-width at half maximum (FWHM) Gaussian kernel by SPM8 software (Statistical Parametric Mapping; http://www.fil.ion.ucl.ac.uk/spm). The first five images of each series were removed from further analysis. Then the data was analyzed with a novel voxel-based method named eigenvector centrality mapping (ECM) according to a recent study (see Lohmann 2010) [10]. ECM attributes an eigenvector centrality value to each voxel in the brain such that a voxel receives a larger value if it is more strongly correlated with many other voxels which are central within the network themselves. The ECM analyses included the following four steps. First, a whole brain mask was defined according to a prior anatomical automatic labeling (AAL) atlas containing 90 areas of n = 40,743 voxels. Second, the time series were extracted from each voxel in the defined mask for each subject. Linear correlation which proposed as a metric of functional connectivity was calculated between any two voxels as follows:

$$r_{ij} = \frac{\sum_{t=1}^{T}\left[x_i(t)-\overline{x_i}\right]\left[x_j(t)-\overline{x_j}\right]}{\sqrt{\sum_{t=1}^{T}\left[x_i(t)-\overline{x_i}\right]^2}\sqrt{\sum_{t=1}^{T}\left[x_j(t)-\overline{x_j}\right]^2}} \tag{1}$$

where $x_i(t), x_j(t)$ $(t=1,...,T=200)$ are the time series of voxel i and j, $\overline{x_i}, \overline{x_j}$ are the mean of the two series. In this way, a similarity matrix A was obtained for each subject in the two resting scans and each r in A was substituted by $\tilde{r}=r+1$ as the similarity matrix should be positive according to the previous study. Then, the eigenvector centrality value x_i of a voxel i is defined as the i-th entry in the normalized eigenvector x belonging to the largest eigenvalue λ of the similarity matrix A, and the formula is as follows:

$$Ax=\lambda x \text{, equivalent to } x=\frac{1}{\lambda}Ax \text{, and } x_i=\mu\sum_{j=1}^{n}a_{ij}x_j \tag{2}$$

where $\mu=\frac{1}{\lambda}$, and a_{ij} represents the element in the i-th row and j-th column of A. For each subject in the two resting scans, an ECM containing the eigenvector centrality value of each voxel in the mask was obtained here. At last, a paired t-test was performed between the ECMs of pre- and post- resting scan. At the statistical analysis level, a voxel-cluster threshold correction was used to control the Type I error rate in the whole-brain statistics, yielding an overall corrected alpha rate of $P < 0.05$. The correction threshold was determined from a Monte Carlo simulation in AFNI and required a voxel-wise threshold of $P < 0.005$ within a minimum 3D cluster of 41 contiguous significant voxels (minimum cluster volume = 1476μl; FWHM autocorrelation estimate = 8.0 mm). The cluster-level inference was performed within SPM8.

3 Results

Fig. 1 shows the whole brain mask defined in this study, containing 90 anatomical automatic labeling (AAL) areas of 40,743 voxels. The group averages of eigenvector centrality maps are illustrated in Fig. 2. For the experimental group, Fig. 2a and 2b show the results of the pre- and post- resting scans respectively. For the control group, the group averages of ECMs in the pre- resting scan are shown in Fig. 2c, and Fig. 2d displays the results of the post- resting scan. After motor imagery training, the significantly increased eigenvector centrality was detected in the precuneus and medial frontal gyrus (MFG) for the experimental group while no significant alterations were found for the control group (see details in Fig.3 and Table 1).

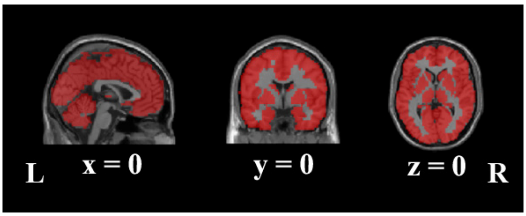

Fig. 1. The mask used in this study, containing 40,743 voxels

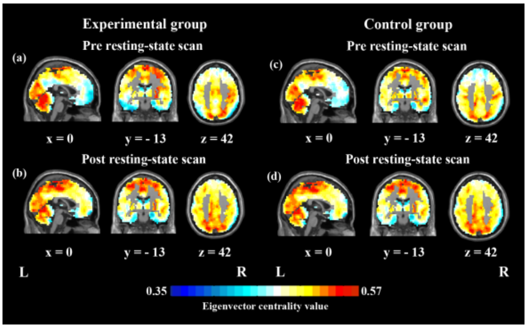

Fig. 2. Group averages of eigenvector centrality maps. (a) pre- resting scan, experimental group; (b) post- resting scan, experimental group; (c) pre- resting scan, control group; (d) post- resting scan, control group.

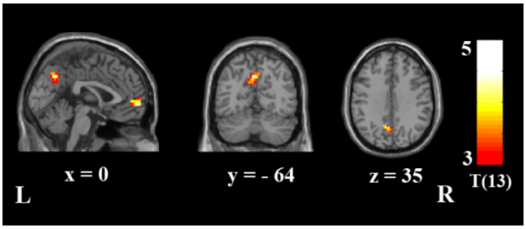

Fig. 3. Statistical parametric map of regions showing eigenvector centrality increased in experimental group induced by motor imagery learning. The statistical threshold was set at $p<0.05$ corrected for multiple comparisons at the cluster level.

Table 1. Brain regions where eigenvector centrality significantly increased in the resting-state after motor imagery training ($p < 0.05$ corrected for multiple comparisons at the cluster level)

Region	L/R	BA	x	y	z	t_{max}
Experimental group						
precuneus	L	7	-3	-64	38	4.27
medial frontal gyrus	L	10	-6	59	2	4.45
Control group						
None						

Note. MNI coordinates; BA—Brodmann's area.

4 Discussion

To address whether motor imagery training affects resting state, we used ECM to investigate the neural changes underlying the resting state associated with 14 consecutive days of motor imagery training with fMRI. Our results revealed that the eigenvector centrality of two brain regions, including the precuneus and medial frontal gyrus (MFG), were significantly increased by the motor imagery training.

Numerous of neuroimaging studies have suggested the important role of precuneus and MFG in motor training. The role of precunues in motor imagery has been suggested by Sakai et al. (1998) that it could be activated when subjects learned sequences of finger movements, indicating that precuneus may be related to spatial motor sequence information integration and retrieval [12]. A Magnetoencephalography (MEG) study by Ogiso et al. (2000) confirmed that the precuneus may involve in retrieval of spatial information and/or setting up spatial attributes for motor imagery [13]. Our previous study also found the activation in precuneus increased after motor imagery training, indicating that the precuneus may be engaged in mental representation and episodic memory retrieval [11]. Therefore, the alteration of precuneus in the current study may due to spatial information processing and retrieval.

Previous studies have suggested that the role of MFG may be involved in inner state modulation and motor planning, as well as complex nonmotor tasks such as decision making, discrimination, computation, and reasoning [14, 15]. The MFG was implied to be associated with the ability to reflect on one's own mental states and self-referential processing such as mediate less-deliberate, emotion-driven influences on action selection [16, 17]. It was also suggested to be important in allowing subject to guide actions by internal or overarching plans so as to achieve an optimal behavior performance [14]. Thus, we proposed that the changes in MFG may be the result of the modulation of subjects' inner state to get an optimal behavior and decisions about motor plans.

The results observed in this study confirmed our hypothesis that there are alterations in the resting state induced by motor imagery training. As a pilot investigation, our result indicated that motor imagery training, as an important part of motor training, is worthy to be further investigated in more details.

5 Conclusion

We used a method named eigenvector centrality mapping to explore the resting-state before and after a 2-week motor imagery training. We found that through motor imagery training, the significant increases of eigenvector centrality were detected in the precuneus and medial frontal gyrus (MFG). These alterations may be related to the spatial information integration or retrieval and inner state modulation during motor imagery training, which further provided new insights into the understanding of the neural mechanism underlying motor imagery training.

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