Motor task-based differences in brain networks: Preliminary results

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***Abstract*— This study examined characteristics of the brain networks related to upper limb grasp movements. EEG signal of 4 patients with chronic stroke were analyzed during different motor tasks. We compared the brain networks involved in the Active and Motor Imagery tasks by using the centrality and small-worldness (SW). There was a statistically significant difference between the centralities of two motor tasks in motor cortices of affected hemisphere in the high beta band (21 – 30 Hz). For SW, the Active task also decreased in the high beta band in contrast with the MI task. In this paper, we could support evidence that brain networks may different under the conditions of different motor tasks in both frequency and temporal domain.**

I. Introduction

Previous studies obtained brain activation by electroencephalography (EEG) channels and compared the EEG power spectra of stroke patients and controls [1]. However, the pathways of various brain regions are still unclear because analysis of EEG power spectra hardly represents interactions in the brain.

In existing studies, they represented brain network properties of stroke during motor tasks [2-4] . Wang *et al*. and Fallani *et al*. analyzed the brain networks of stroke patients using the finger-tapping test [4, 5]. Fallani *et al*. and Yan *et al*. studied the Motor Imagery (MI) network [6, 7]. Most existing studies analyzed each pattern of brain network according to type of motor tasks as the Active and MI tasks rather than identifying the distinction between the Active and MI tasks.

Thus, we focused on examining this difference of network characteristics between the Active and the MI tasks. We mainly hypothesized centrality and SW of the Active task are bigger than those of the MI task with primary motor cortex as the center because our protocol focused on motor execution.

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II. Method

A. Participants

Four stroke patients with upper limb monoplegia participated in this study. They had not individual difference by entering stable state of neuroplasticity [mean (standard deviation) age: 53.25 (5.5); years; 2 male and 2 female patients; Fugl-Meyer Assessment (FMA): 44.25(10.78), (Rt. 4)]. With approval by Institutional Review Board of both Korea Institute of Science and Technology (KIST IRB; KIST 2013-009) and Samsung Medical Center (SMC IRB; SMC 2013-02-091), the participants enrolled and conducted the experiment at SMC. The inclusion criteria of participation were chronic stroke patients at least 3 months or more after onset with ages between 40 and 70 years. Patients with artificial pacemaker or with complaints of claustrophobia, pain from acupressure during the EEG experiment, or a decline of perception and an inability to follow the instructions of the researchers were excluded from this study.

B. Experimental design

In order to obtain the characteristics of brain networks of chronic stroke patients during upper limb movements for rehabilitation, participants performed grasp movements with the affected hand by collecting their EEG signals. The haptic device in the experiment was controlled by a DSP processor, as shown in Fig.1, and it was synchronized with a stimulation program by Flash™. This stimulus of haptic was connected to EEG System (sampling rate: 2048 Hz; Active-two, Biosemi™, Amsterdam, Netherlands). The system was developed by KIST and described in the previous study [8].

In experiment protocol, participants performed three different motor tasks: the Active task in which the participants performed the exercise themselves, the MI task in which they imagined the movement, and the Passive task driven by the device. All trials for a participant were consisted of nine sets (3 sets per motor task). In this study, however, we only used the data for the Active and MI tasks to compare this two motor tasks. The experiment was conducted as shown in Fig.2, where the participants had to fix their gaze on the monitor. They then conducted the motor task for two second after the cue, held the movement for one second, and finally, returned to their original state during the “return phase”.

Figure 1. Haptic device. (In this study, participants performed upper limb motor task as grasp movement.)

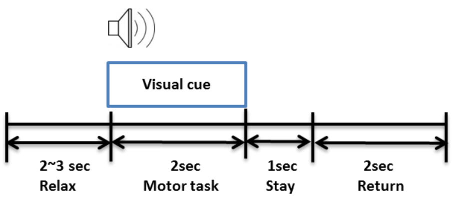


Figure 2. Experimental design. (In this study, participants randomly performed motor task after cue)

C. *Analysis*

- EEG data preprocessing

After the 64 channels of EEG were down sampled to 256 Hz, data were subjected to band-pass filtering from 1 to 80 Hz, and time extraction from -4 to 6 second. Noisy signals from the outside were removed by the EEG lab toolbox and applied to the Common average reference (CAR). The 64-channel EEG data that passed the above manipulations were separated into various frequency bands [mu (8 - 12 Hz), low beta (13 - 20 Hz), high beta (21 - 30 Hz), and gamma rhythm (31 - 50 Hz) that are related to sensorimotor rhythm].

- Brain connectivity & graph theory analysis

In order to determine correlations within the widely distributed neural networks, we calculated the phase synchronizations between two EEG channels with the phase locking value that calculates the phase difference by extracting the component of the signal phase [9]. Also we set time window as 1 second after extracted data from -1 to 5 second, and analyzed the brain networks with the basic parameters of graph theory index, including the centrality and SW properties which formulas are described below [10]. Then, we set baseline from -1 to 0 second, and compared statistically graph theory index of each time window and baseline.

i. Centrality

Centrality indicates the relative importance of a node in the network. Thus, in this study, we used the node degree, which is the basic parameter measuring centrality. The node degree is obtained by the number of link connections between each node.

$$k_i = \frac{1}{n}\sum_{j\in N} a_{ij} \quad (1)$$

k_i: Degree of node i

a_{ij}: Connection status between i and j

ii. Small-worldness

The properties of SW in a brain network indicating vigorous communication and greater efficiency in transmitting information is acquired by the next formula. This value is acquired by the clustering the coefficient and the characteristic path lengths, and this index value is bigger than 1 if the network of each group has SW properties.

$$\mathrm{SW} = \frac{C/C_{rand}}{L/L_{rand}} \quad (2)$$

$$\mathrm{C} = \frac{1}{n}\sum_{i\in N} C_i = \frac{1}{n}\sum_{i\in N}\frac{2t_i}{k_i(k_i-1)} \quad (3)$$

C : clustering coefficient

C_{rand} : clustering coefficient of random network

$$\mathrm{L} = \frac{1}{n}\sum_{i\in N} L_i = \frac{1}{n}\sum_{i\in N}\frac{\sum_{j\in N, j\neq i} d_{ij}}{n-1} \quad (4)$$

L : characteristic path length

L_{rand} : characteristic path length of random network

III. RESULTS

In this study, we highlighted the centrality and SW in order to find the differences between the Active and MI tasks.

To establish appropriate frequency bands that have significant difference of graph theory index between the Active and MI tasks according to time window, we performed two sample t-test (p<0.05) between motor tasks of the node degree and SW on C3. That is primary motor cortex in affected hemisphere and relate to movement of our protocol. Table Ⅰ shows the p-value of graph theory index depending on each frequency bands. There is statistically significant difference between two motor tasks in the high beta band.

TABLE I. SIGNIFICANT FREQUENCY BAND IN MOTOR TASK PHASE

***p*-value**	**Frequency band(Hz)**			
	Mu	***Low beta***	***High beta***	***gamma***
Node degree	0.1964	0.7497	0.0291*	0.1222
SW	0.3538	0.3918	0.0106*	0.2534

*. p<0.05

For centrality, we found change in the node degree distribution for each time window of motor execution phase compared with baseline. The second and third column of Fig.3 represents the difference based on baseline in the topoplots in the high beta band. The red color indicates increasing values compared with baseline, and blue color indicates decreasing values. In visual inspection, the node degree of Active on affected hemisphere is increased in the initial motor task phase (0 - 1 s), and shift to unaffected hemisphere as time goes on. On the other hand, those of MI task have different characteristics.

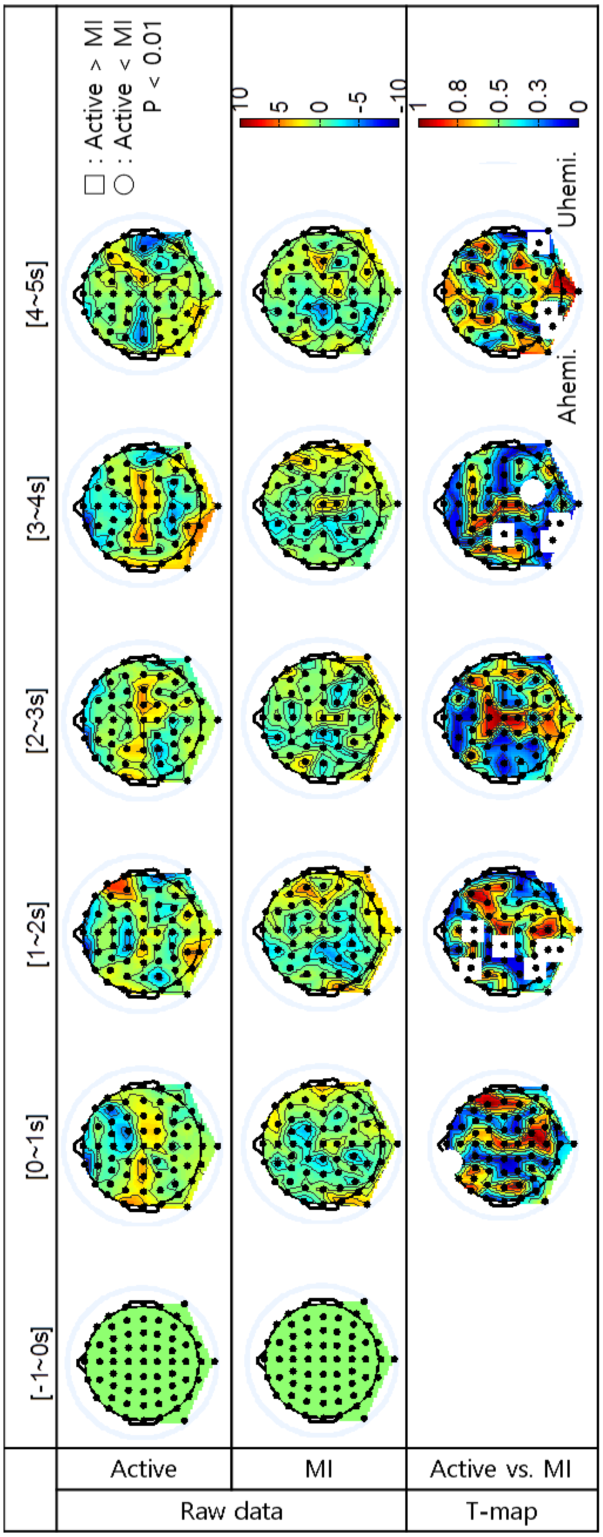
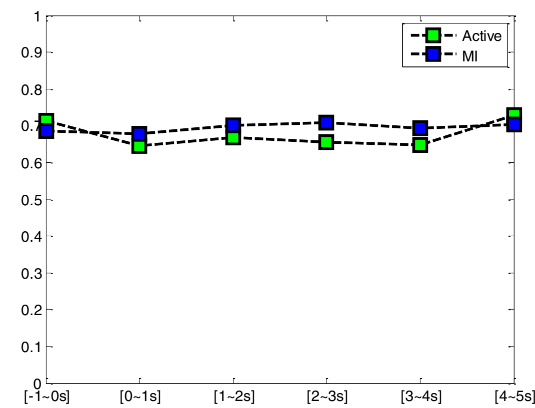


Figure 3. Differences in the node degree distributions and t-map. (Right hemisphere is contralateral side and left hemisphere is ipsiliateral side for affected hand.)

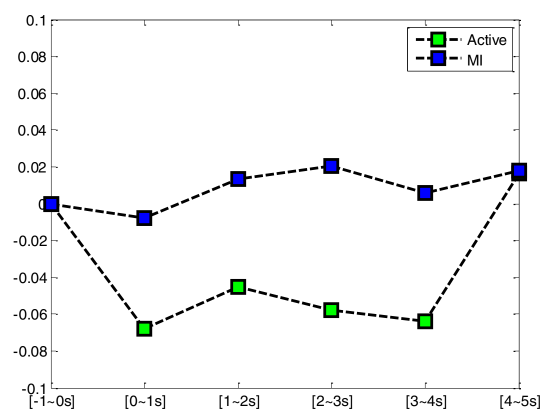
To identify statistical difference of network characteristics between the Active and MI tasks, we performed two sample t-test (p<0.01). The forth column of Fig.3 represents significant channels according to two motor tasks in each time window of the high beta band (21 - 30 Hz). In t-map, the square spot means that the node degree of the Active task is bigger than the MI task in each time window, and circle spot is contrast to that.

Although there is no significant difference between two motor tasks in initial motor task phase, t-map during [1 - 2 s] in Fig.3 shows that the node degree of the Active task is statically bigger than MI task in affected hemisphere. Also parietal area during [3 - 4 s] and [4 - 5 s], “return phase” of grasp movement, is significantly bigger than MI task.

Next, in order to find the properties of SW, we calculated the values of SW with clustering coefficient and characteristic path length, and the results are shown in Fig.4. The X-axis of Fig.4 represents the time window, and Y-axis of Fig.4(a) means value of SW and of Fig.4(b) means the change in the high beta band. Also the green squares are the values in the Active task, and the blue squares are the values in the MI task.



(a)



(b)

Figure 4. The value of “small-worldness(SW)” of motor task in the high beta band (21 - 30 Hz). ((a) represents value of SW, and (b) shows the difference of SW depending on baseline [0 - 1 s]. Green squares indicate SW

of the Active task and blue squares indicate SW of the MI task. SW of the MI task is higher value than the Active task in the high beta band.)

Fig.4(a) shows that values of SW in the Active and MI tasks are smaller than 1, which is generally minimum value for properties of SW. Fig.4(b) represents that the change of SW depending on baseline (-1 - 0 s) of the Active task is lower than that of the MI tasks. There are no significant difference of SW between Active and MI tasks according to each time window. However, SW of the Active task decrease based on baseline, whereas those of the MI task remain unchanged in visual inspection.

IV. DISCUSSION

In this study, we hypothesized that there would be differences in properties of the networks in the Active and MI tasks according to time window, and we found differences as to centrality and SW.

Firstly, we found the high beta band (21 - 30 Hz) have meaningful area between the Active and MI tasks in motor execution phase. Our result is in the line with the study of Gross *et al*., whose results represented the strong different task-dependent variations between static and dynamic condition in primary motor cortex and SMA during finger tapping in the beta band (13 - 24 Hz) [11].

Secondly, centrality of the Active task increase in motor cortex as like existing studies in fMRI and signal power analysis [1, 3]. However, the MI task do not represent similar characteristics. On the basis of difference above, phase of [1 - 2 s], end point of motor execution, have statistical difference in the affected hemisphere (p<0.01).

Thirdly, SW of two motor tasks in our study do not have properties of SW, even if Jin *et al*. represented that healthy group have properties of SW during rest and motor task [12]. Perhaps, this results are because of collapse in neural network by stroke [3]. Also, in contrast with centrality, SW of the Active task show the trend to be decreased depending on baseline, whereas the MI task have little change. This results show that brain network of the Active task have time-dependent properties than those of the MI task.

In this study, we show different mechanism of the Active and MI tasks even if these motor tasks are focused on motor function. If both Active and MI tasks have motor intention, we want to obtain motor intention by comparing Active and MI tasks. Therefore, we expect to apply our results, which have significant temporal-dependent difference of two motor tasks, to BCI-rehabilitation system for stroke patients.

V. CONCLUSION

We found differences of the networks properties involved in the Active and MI tasks with respect to centrality and SW. Based on our analysis for the brain networks of stroke patients, we were able to explain the possibility depending on the temporal change of brain network between the two motor tasks in the high beta band. Based on these results, we will research brain networks with more quantitative parameters and methods, and to compare stroke patients and healthy control group for further study.

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