Estimation of brain dynamics under visuomotor task using functional connectivity analysis based on graph theory

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Phuong Thi Mai NGUYEN[1], Xinzhe LI[2], Yoshikatsu HAYASHI[2], Shiro YANO[1], and Toshiyuki KONDO[1]
[1] *Department of Computer and Information Sciences, Tokyo University of Agriculture and Technology*, Tokyo, Japan
phuong@livingsyslab.org, syano@cc.tuat.ac.jp , t_kondo@cc.tuat.ac.jp
[2] *School of Biological Sciences, University of Reading*, Reading, RG6 6AH, UK
xinzhe.li@pgr.reading.ac.uk, y.hayashi@reading.ac.uk

***Abstract*— Network studies of brain connectivity have demonstrated that the highly connected area, or hub, is a vital feature of human functional and structural brain organization. Hubs identify which cognitive region plays an important role in each task. In addition, a complex visuomotor learning skill causes specific changes in activation across brain regions. Accordingly, this study utilizes the hub as a feature to map the visuomotor learning tasks and their dynamic functional connectivity (dFC). The electroencephalogram (EEG) data recorded under three different behavior conditions were investigated: motion only (MO), vision only (VO), and tracking (Tra) conditions. Here, we used the phase locking value (PLV) with a sliding window (50 ms) to calculate the dFC at four distinct frequency bands: 8-12 Hz (alpha), 18-22 Hz (low beta), 26-30 Hz (high beta) and 38-42 Hz (gamma), and the eigenvector centrality to evaluate the hub identification. The Gaussian Mixture Model (GMM) was applied to investigate the dFC patterns. The results showed that the dFC patterns with hub feature represent the characteristic of brain at visuomotor coordination behavior.**

Keywords— EEG, visuomotor learning, dynamic functional connectivity, eigenvector centrality.

I. INTRODUCTION

Recently, there are many studies considering dynamic functional connectivity (dFC) as a promising subfield [1] [2] [3] [4] [5]. Brain functional connectivity undergoes dynamics changes from the awake [6] to the unconscious. Although many studies are demonstrating the dynamic functional connectivity in consciousness, few studies have investigated changes in anticipatory mechanisms measured by both visuomotor coordination and EEG functional connectivity during time paradigms of modular learning [7]. This study examined the correlation between dynamic functional connectivity and visuomotor coordination behavior.

Furthermore, we identified which brain areas were involved in visuomotor coordination. It defined the sensory, motor, and visual regions as the regions of interest (ROIs). This study differs from other EEG research in that we used the feature named "brain hub", which was characterized by its high degree of connectivity to other regions and its central placement in the network [8]. A hub is a new approach to the identification and classification of putative hub regions in brain networks base on multiple network structural embedding of such areas and their functional roles. In terms of identification of hub nodes, there are several variations of centrality metrics. In this work, we chose to apply eigenvector centrality (EVC) because it incorporates the entire graph structure in determining the relative importance of each node in the network [9] [10] [11]. We used a hub as a feature for dynamic spatial patterns, or state, classification. The dFC states have been found across time and subjects by the unsupervised machine learning technique - Gaussian Mixture Model classification.

In this study, we address this problem by utilizing an existing dataset from Reading University with simultaneous EEG signal. The data were collected both during motion only, vision only and tracking trials on a small sample of 10 subjects. By far, the most common strategy to study dFC based on computing the phase locking value between each pair of brain regions over window times. The reoccurring dFC states have been found across time and subjects by employing GMM clustering algorithm. This study has two primary purposes: (1) to understand the dynamic transition of the EEG functional connectivity related to the difference experiment behavior tasks and determine which state are the most contribution for the difference; (2) to explore the cortical region of hub which play an essential role in the organization of the overall networks in these tasks.

II. MATERIAL

A. Participants and experiment protocol

Twelve right-hand and healthy subjects took part in this experiment (4 males, 8 females, all right-handed, between 19 and 24 years old). All of subjects were students at the University of Reading. The experiment was approved by the Ethic Committee of School of Systems Engineering, University of Reading. Behavioral tasks included three experiment conditions, which are motion only condition (MO), vision only condition (VO) and tracking condition (Tra). The participants sat comfortably in an office chair and took in a total of 60 trials for three conditions. The trial time was 40 seconds, while there were 10 seconds between each trial. Participants first performed Tra, then MO, and finally VO trials. In Tra condition, participants were asked to move the track a red-dot target, which moved in a circular trajectory with a constant speed, with a tracer. In the MO condition, participants were asked to move the tracer in a circular path at an arbitrary but constant speed while the target not shown. In the VO condition, participants did not take control of the tracer. Recorded position of the target and tracer form previous tracking trials would be played on the screen, with both tracer and target are shown.

B. ROIs selection

This study defined four ROIs according to Broadman's area: primary motor cortex (FC3, FC1, C5, C3, C1, CP3 are ROI_1), pre-parietal somatosensory association cortex (C3, C1, Cz, CP1, CPz are ROI_2), superior parietal somatosensory association cortex (CP3, CP1, P3, P1, Pz are ROI_3), and primary visual cortex (PO3, POz, PO4, Oz are ROI_4).

C. EEG data preprocessing

EEG data were processed by applying MATLAB and EEGLAB (Swartz Center for Computational Neuroscience, La Jolla, CA). First, the data were band-pass filtered (0.1-50 Hz, EEGLAB embedded FIR filter), then the filtered time series were cut into trials. After that, an independent component analysis (ICA) was performed on the data to remove eye blinking and other artifacts. The whole trial would be rejected if more than 50% of ICs were recognized as artifacts. After ICA analysis step, the data were processed with the Laplacian operator through CSD toolbox. This processing is aimed to avoid the phase synchronization resulted from both electrodes sharing a common source.

III. METHODS

Most human actions require the integration of numerous functional areas widely distributed over the brain. The underlying mechanism behind this large scale network is generally described by the term functional connectivity. The functional connectivity is studied by considering the similarities between the time series or activation maps. The time resolution of EEG is high enough to access a dynamic of brain network activity. Various measures of synchronization, such as synchronization likelihood and phase synchronization, had been proposed to detect the general interdependencies. Synchronization is also believed to be a central mechanism behind the interaction between brain areas [12]. In this study, the phase synchronization between recorded channels in defined frequency, namely frequency range in alpha (8-12 Hz), low beta (18-22 Hz), high beta (26-30 Hz) and gamma (38-42 Hz) bands. Employed synchrony, called phase locking value (PLV), was introduced by [13].

A. Brain dynamic functional connectivity using PLV

A functional connectivity metric known as PLV depends on the instantaneous phase of signals. The assumption is that if two brain regions are functional connected, the difference between the instantaneous phase of the signals from these regions should remain or less constant. In this study, the used phase locking index is the phase locking value, which is calculated by the equation below.

$$PLV(f,t) = \left| \frac{1}{\delta} \int_{t-\frac{\delta}{2}}^{t+\frac{\delta}{2}} exp\{i\theta(f,t)\} \right| \quad (1)$$

Where $\theta(f,t)$ is the instantaneous phase of two signals and δ is the time window where each PLV are calculated. There is no phase locking if the PLV varies from 0. Versus, the phases are completely locked when PLV is equal to 1. To build a fully connected graph, a threshold θ (highest 10%) to remove quick connections of the functional connectivity metric [14]. It was used to threshold the correlation matrix into the adjacency matrix $A = (a_{ij}), 1 \le i,j \le N$ of a metric PLV:

$$a_{ij} = \begin{cases} 1 & , PLV_{ij} \ge \theta \\ 0 & , PLV_{ij} < \theta \end{cases} \quad (2)$$

B. Graph theory

A graph is a mathematical object that can be used to represent networks, especially brain network. The channels are the graph nodes, and edges represent the functional connectivity between those connected channels. In this study, we describe a measure that detects aspects of global brain connectivity and quantifies essential of an individual brain region. To examine the dynamic functional connectivity, PLV was calculated by using sliding time window 50 ms.

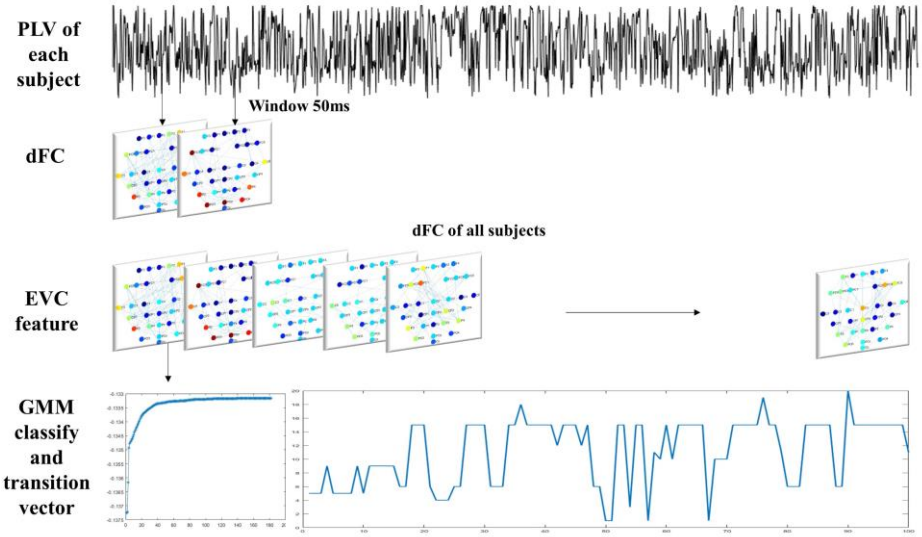

Fig. 1. Schematic depicting computiation of the dFC states. First, the dFC matrices of individual subject are computed on windowed portions by PLV. Then, dFC states of all subjects are classified using GMM algorithm with EVC feature.

Furthermore, the network analysis of brain connectivity was used to identify sets of regions that are critically important for enabling efficient neuronal signaling and communication. The EVC specify specifically weights nodes based on their degree of connection within the network. It does so by counting both the number and quality of links so that a node with few connections to some high-rank other nodes may outrank one with a larger number of mediocre contact [15]. Google's PageRank algorithm is a variant of EVC [16]. The EVC was introduced by Bonacich [17]. This is simply the first eigenvector of the adjacency matrix A, which corresponds to the largest eigenvalue λ_1:

$$EVC(i) = \frac{1}{\lambda_1} A\mu_1 = \frac{1}{\lambda_1} \sum_{j=1}^{N} a_{ij}\mu_1(j) \qquad (3)$$

These produces estabilish undirected and weighted networks — the nodes defined as 'hub' whose EVCs are above the thresholds. The mean EVC thresholds across subjects were calculated with the highest 10% [18]. We then applied the Gaussian Mixture Model to identify reoccurring connectivity pattern, which we defined as dynamic functional connectivity states (dFC states) (Fig. 1). Because dFC states reoccur across time and the subjects, the clustering algorithm was applied to the set of all subjects in three behavioral tasks ($tasks \times subjects \times windows$). The number of states was determined automatically by using the variational Bayesian model selection [19]. We repeated the clustering algorithm 50 times to increase the chances of escaping the local minima.

In addition to describing the connectivity differences that distinguish dFC states, we also examine their occurrence as a function of time and the transition between them. The dFC states have been investigated in a variety of studies, which have shown that the dFC states are associated with ongoing cognition, consciousness level, flexible behavior. A current new perspective suggests that the abundance of the brain's dynamic repertoire facilitates novel cognition and behaviors, making it possible to adapt to external task demands rapidly and efficiently [20]. The dFC states transitions resulting in the abundant shape of brain connections that are required to assist in behavior task performance. Therefore, we hypothesized that the activity of brains might have a different transition frequency of dFC states for different task performance. Differences in the reoccurrence time of each dFC state for every behavior task was examined using Chi-square tests.

IV. RESULT

A. *The behavior tasks related to brain functional network*

The classification was trained with the EVC feature of all subjects and all behavior task conditions. The dynamic functional connectivity networks were pooled together and clustered into 20 clusters as 20 states. For each subject, the property of all dFCs was examined: the reoccurrence times of all the dFC states. We used Chi-square tests revealed significant differences in the reoccurrence times of the states between three conditions in four frequency band. From the result in Table I, the reoccurrence time of dFC states and behavior tasks were statistically significantly associated with

TABLE I. CHI SQUARE TEST RESULT

Frequency band	$\chi^2(df = 38)$	$p - value$
8-12Hz	482.85	< 0.01
18-22Hz	298.09	< 0.01
26-30Hz	256.81	< 0.01
38-42Hz	646.08	< 0.01

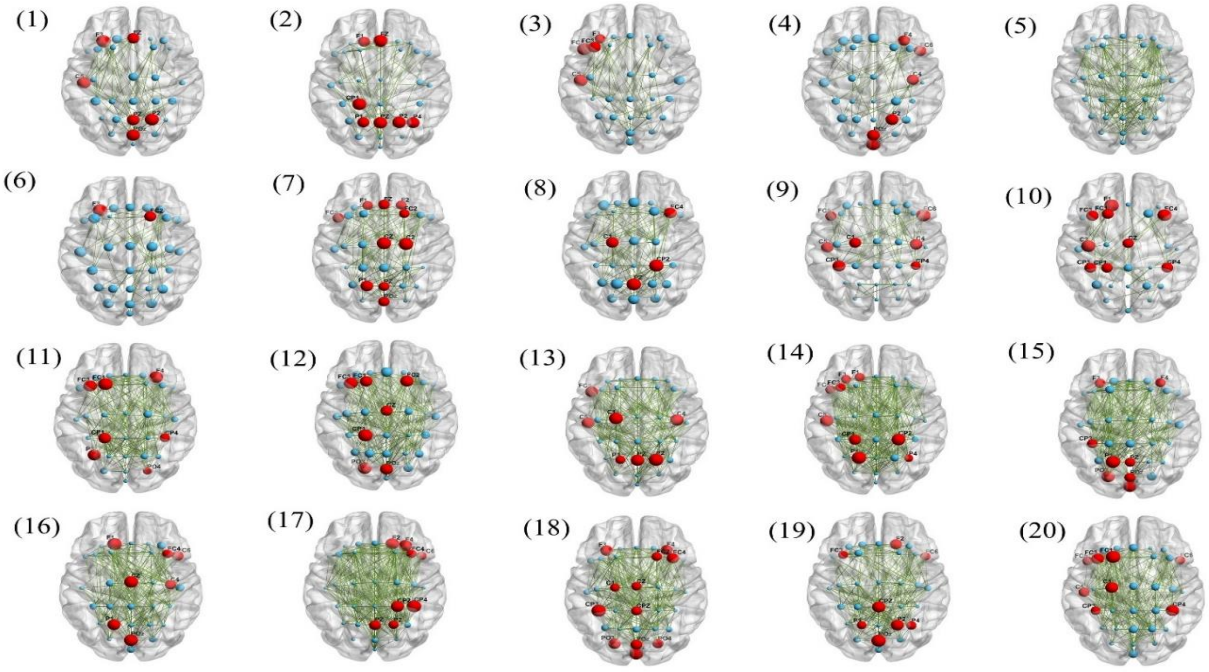

Fig. 2. There are 20 dFC patterns of classifacation result.

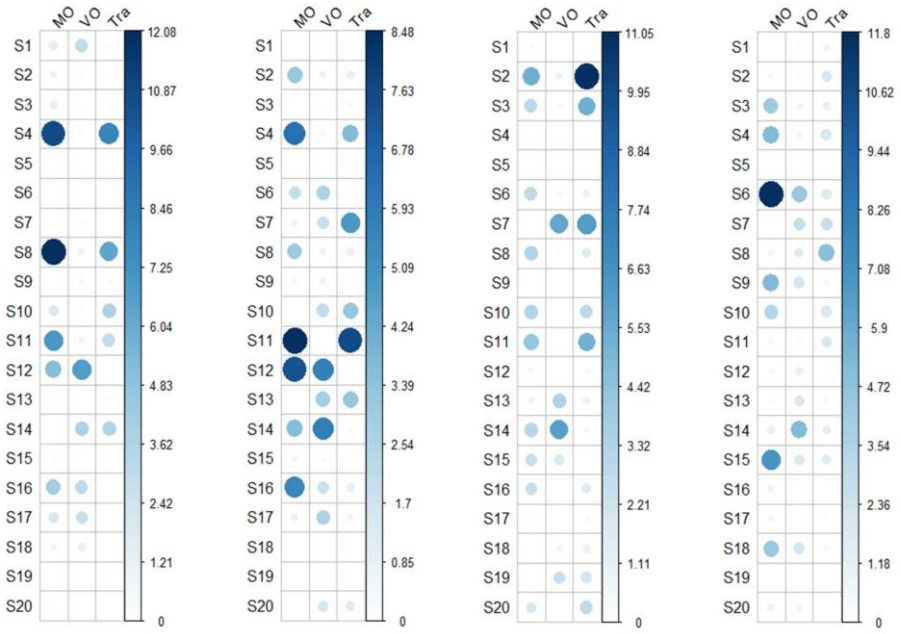

Fig. 3. The Chi-square contribution differene result for 4 frequency band: alpha, low-beta, high-beta and gamma. Blue color represented for contribution ratio.

the level of significant 1% ($\chi^2 = 482.85$ for alpha, $\chi^2 = 298.09$ for low-beta, $\chi^2 = 256.81$ for high-beta, $\chi^2 = 646.08$ for gamma, all of $p - value < 0.01$).

Another approach, based on the Chi-square contribution, tell us which dFC states contribute most to a particular outcome for each frequency band. The result was shown in Fig. 2 and Table II. These cells of Table II contributed more 50% to the total Chi-square score and thus account for most of difference between three conditions. In alpha wave band, MO and Tra had same states 8 and 4. In these states, the alpha synchronization almost occurs in the right hemisphere. While with VO, alpha synchronization occured in the left at the primary motor cortex, somatosensory association cortex, and visual cortex. In beta, MO and Tra continuously share the state 11, while VO and Tra have the same state 7 in a high-beta. In gamma band, three conditions were utterly different. State 14 is essential with VO condition because it appears in three frequency bands.

B. Important network regions defined by hubs

To have a better understanding of the characteristics of the dFC, we identified as "hub" the node with 10% highest EVC for each state. The hub, which plays a vital role in the organization of the overall networks [21], is the node with EVC above or below a threshold computed by the statistical quartile for each behavior tasks. Fig. 3 shows the hub structures of 20 dFC states. To identify cortical regions of the hub, we used Monte Carlo analysis to calculate the overlapping area of the hub for each state. Finally, we assessed whether the hub patterns within the ROIs could be characterized the task conditions. To test the appearance of hubs on ROIs, we used the F-test across the subjects, and the result was shown in Table III The overlapping regions were high on ROI_1 at all three task conditions. The p-value for the test of hubs appearance was less than the level of significant 5%. There were the same hubs in the ROI_3 at motion task and vision task at the high-beta. Hubs did not appear in ROI_4 at all tasks. The difference is in the ROI_2. When vision conditions only had the hubs in an alpha, others condition had the hubs in three wave bands, low and high beta, gamma for motion condition and alpha, low beta, gamma for tracking condition.

V. Discussion

Currently, there are many studies to examine how differences in dFC between different contexts relate to cognitive demands and behavioral performance [1] [22] [23]. Our analysis of dynamic functional connectivity follows these ideas. In this study, we employed a visuomotor coordination behavior approach to analyze the brain dynamic functional connectivity. EEG data of three behavior tasks which had similar and different characteristics were used. The MO had the same motion as Tra and participant received the same sensory feedback as they were touching the haptic device. However, there were not any target on display; the participants did not have the visual feedback, versus from VO. Tra was the combination of MO and VO. Hub represented for the channels which had high synchronization.

TABLE II. THE STATES HAVE THE CONTRIBUTION DIFFERENCE OVER 50% FOR EVERY CONDITION TASKS AND FREQUENCY BAND.

	8-12Hz	18-22Hz	26-30Hz	38-42Hz
MO	S8 (12.08%), S4 (10.79%), S11(6.56%)	S11(8.48%), S12 (7.36%), S4 (6.31%), S16 (5.49%)	S2 (5.38%), S11(4.28%)	S6 (11.80%), S15 (6.93%), S4 (5.12%), S18 (4.46%), S3 (4.18%)
VO	S12 (6.73%)	S14 (5.84%), S12 (5.71%)	S14 (5.99%), S7 (5.99%)	S14 (5.19%), S6 (4.48%)
Tra	S4 (7.86%), S8 (6.33%)	S11 (7.57%), S7 (4.86%)	S2(11.05%), S7 (6.19%), S3(5.37%), S11 (5.25%)	S8 (4.90%)

TABLE III. THE P-VALUE FOR APPEARANCE EVC HUBS BY USING F TEST IN EACH FREQUENCY BAND AND THREE BEHAVIOR TASKS. THERE IS HUB AT THE REGION WHICH HAS P-VALUE SMALLER THAN 0.1.

	MOTION ONLY (MO)				**VISION ONLY (VO)**				**TRACKING (Tra)**			
	ROI_1	*ROI_2*	*ROI_3*	*ROI_4*	*ROI_1*	*ROI_2*	*ROI_3*	*ROI_4*	*ROI_1*	*ROI_2*	*ROI_3*	*ROI_4*
8-12Hz	**0.0755**	0.1171	0.4129	0.4966	**0.0064**	**0.0079**	0.1542	0.7057	**0.0425**	**0.0532**	0.2853	0.4455
18-22Hz	**0.0163**	**0.0810**	0.1209	0.7057	**0.0092**	0.1767	0.4244	0.6538	**0.0067**	**0.0028**	0.4577	0.8137
26-30Hz	**0.0329**	**0.0769**	**0.0256**	0.4456	**0.0014**	0.1214	**0.0178**	0.4733	**0.0020**	0.3258	0.1799	0.9998
38-42Hz	**0.0115**	**0.0115**	0.2027	0.6849	**0.0219**	0.2751	0.3308	0.4810	**0.0384**	**0.0731**	0.2427	1

The values in BOLD highlight the regions with p-value less than 10%.

Our result suggests that the hub of dynamic functional connectivity patterns might remain the similarities and the differences of characteristics in visuomotor coordination behaviors. The most central brain regions are in the primary motor cortex. Synchronized activity in the primary cortex is modulated in the alpha, beta, and gamma frequency bands during various stages of movement planning and execution [24]. A significant difference is in superior parietal somatosensory association cortex. MO and Tra have the hub in low-beta and gamma wave band at this region. While VO and Tra have the hub in alpha wave band. A central role for pre-parietal flexible hubs in cognitive control of task demands [25]. That results show that the dFC patterns with hub feature represent the characteristic of brain at visuomotor coordination behavior.

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