Functional brain networks related to working memory using phase synchrony analysis

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Abstract— **Phase synchrony among cortical brain regions is a key aspect of the working memory process. In this study we utilized phase synchrony analysis of EEG signals to construct brain networks and investigate the rest and working memory states of the brain. The maintenance period of working memory demonstrated higher global and local phase synchronization compared to the rest condition in the theta, alpha and beta bands. In contrast, during the manipulation period, we observed high synchrony between brain areas in the theta band and low phase synchrony in the alpha and beta bands. These alterations between different phases of working memory illustrated the critical behavior of brain networks and their highly dynamic characteristic.**

Keywords-Working memory, brain networks, phase synchrony.

I. INTRODUCTION

Working memory (WM) refers to the preservation of information for a short period of time, a fundamental function for a lot of cognitive procedures [1]. In many studies, different approaches like EEG, fMRI, and MEG have been employed to detect activation of different brain regions during the working memory procedure [2]-[6]. Many of the EEG studies, investigating the spectral changes in brain electrical activity reported a significant increase in theta band oscillations, especially in the frontal lobe, due to working memory [2], [4], [6]. fMRI studies, examining the activation of precise brain regions, have identified the following areas as the most important ones in the procedure of working memory, specifically in N-back task: lateral premotor cortex; dorsal cingulate and medial premotor cortex; dorsolateral and ventrolateral prefrontal cortex; frontal poles; and medial and lateral posterior parietal cortex [3].

Although there are numerous reports about working memory which study activation of distinctive brain regions, investigating the interactions between these regions, known as brain connectivity or brain network [7], has been examined infrequently. This connectivity has been categorized into three distinctive groups: structural, functional, and effective [8].

Graph theory is used to study topological features of brain networks where networks are consisted of vertices, denoting cortical areas in the brain, which are linked by edges, representing connections between the brain regions. Generally, based on some graph measures, i.e. clustering coefficient, a measure representing the connectedness of adjacent nodes around a particular node, and global efficiency, an index displaying the ability of network for communication between distant nodes with few connections, three types of networks has been described [9]: regular, random and small-world networks. In contrast to regular networks with a high clustering coefficient and a low global efficiency, random networks have a low clustering coefficient with high global efficiency [7]. The third class, which is called small-world, is defined by a high clustering coefficient and high global efficiency [10]. Brain networks have been described as small-world graphs, which have the merits of both local and global integration [9], [10].

Recently we investigated the effective brain networks of N-back working memory task [6]. In our previous work, we analyzed the effective brain connectivity associated with working memory by employing the casual modeling of EEG signals without using network measures for quantifying the resulted graphs. In this paper, we aimed to use phase synchronization to compute functional connectivity and calculate some basic graph measures. We explored variations in the topology and structure of functional brain networks and their corresponding measures while subjects participated in a working memory task.

II. MATERIALS AND METHODS

A. Subjects, stimuli, and data recording

10 right-handed male subjects with a mean age of 23.8±2.4 participated in this study. All subjects were healthy university students with normal vision and free from neurological disorders. 3 participants were excluded from further analysis due to low quality of signals in some channels. Each subject gave a written consent after being informed of the task procedure.

We used the N-back task to investigate the effects of working memory. We used 9 English letters and every letter was presented for 500ms by inter-stimulus interval of 1700ms detected by a fixation cross appeared on the screen. Participants were asked to monitor the stimuli and push a button if the presented letter was similar to the one presented N trials earlier where N was 1 and 2. In the 0-back condition participants simply pushed the button when the current letter was an X. The full experiment consisted of 3 sessions and each session consisted of 4 randomized blocks including 3 N-back tasks (i.e. 0-back, 1-back, 2-back) and a baseline (rest). Each N-back block in which 30 letters (10 targets) was shown lasted 66secs and the rest block was considered with the same length. During the rest condition, participants were asked to keep their eyes open, fixating on a cross appeared on the screen, and be relax. Similar to N-back conditions, the rest state was divided into trials with the same length of N-back ones, after data collection, for considering the non-stationary behavior of EEG signals and ease of analysis.

EEG was recorded with Ag/AgCl electrodes at 30 scalp locations based on the standard 10-20 system with ASA-Lab EEG/ERPs 64 Channel Amplifier (Advanced Neuro Technology, The Netherlands). The average of left and right mastoid signals was selected as the reference. Data was sampled at 512 Hz and electrode impedances were kept less than 5kΩ during all recordings.

B. Phase synchrony index

In order to evaluate the relationship between phases of two time series, we use phase synchronization index. We were interested in methods which can separate phase and amplitude component, since phase of any signal carries distinctly different information from amplitude [11]. Phase synchrony measure is able to separate phase and amplitude effects and also take the non-stationary nature of brain activity into account. The complete description of phase synchrony extraction method is available in [11], however we provide a brief introduction of discuss the general aspects.

Let us consider $m(t)$ and $n(t)$ as two signals, oscillators in this context. The scalar signal $m(t)$ can be described in its analytic form [11].

$$m_{\mathrm{an}}(t) = m(t) + i m_{\mathrm{H}}(t) \tag{1}$$

in which $m_{\mathrm{H}}(t)$ is the Hilbert transform of signal $m(t)$. Instantaneous phase of signal $m(t)$ is represented by

$$\phi_m(t) = \tan^{-1}\left(\frac{m_{\mathrm{H}}(t)}{m(t)}\right) \tag{2}$$

Doing the same procedure for signal $n(t)$, relative phase synchrony, for noisy and weakly coupled chaotic oscillators between the same frequencies, may be defined as follows:

$$\varphi(t) = \left|\phi_m(t) - \phi_n(t)\right| \tag{3}$$

where $m(t)$ and $n(t)$ can be considered as the signals of two EEG channels. Next, we compute the distribution of $\varphi(t)$. In fully coupled signals this distribution is like a delta function and any deviation from this will weaken the synchrony. To quantify this concept, phase synchrony index has been formed as

$$PSI = \frac{E_m - E}{E_m} \tag{4}$$

E is the Shannon's entropy of the distribution of $\varphi(t)$ and E_m is the maximum possible entropy with the same bins of $\varphi(t)$ distribution, which obviously belongs to a uniform distribution. PSI is between 0 and 1, representing non-synchrony and perfect synchrony, respectively.

C. Data analysis

Recorded signals were filtered with a band pass (0.5-49 Hz) filter. T7 and T8 Channels were discarded due to an unknown artifact observed in some subjects. This elimination did not have any significant effect on our study as we had six other electrodes near the temporal lobe for assessing the activity of this region. In addition, POz channel was neglected in the network analysis since we wanted to maintain a relatively similar distance between electrodes used as network vertices. With this in mind, 27 remaining EEG channels were employed to construct brain graphs. Next, trials in which signal values exceeded a 70μV threshold were removed. Although the data recording was performed for all conditions, here we compare only the 2-back task with the rest condition. We used the non-target trials of 2-back condition as we were interested to remove the effect of motor activity on working memory networks.

For each condition, rest and 2-back, artifact free and filtered signals were filtered in four known frequency bands; Theta (4-7 Hz), Alpha (8-12 Hz), Beta (13-30 Hz), and Gamma (31-49 Hz). For each trial, PSI was computed between all electrode pairs, resulting in a symmetric 27×27 adjacency matrix. Additionally, in 2-back condition, we divided each 2200ms trial into two consecutive non-overlapping parts. This modification was done to evaluate the effects of manipulation and maintenance of information which are dominant in first and second parts respectively. Next, the network parameters, clustering coefficient and global efficiency, were calculated using Brain Connectivity Toolbox [9]. In order to obtain less noisy and outlier parameters, we first averaged among the adjacency matrix of five consecutive trials and then computed the network measures. We obtained 18 parameters for the rest and 2×18=36 parameters for the 2-back condition.

In this study, fixed edge density method was employed to select the significant connectivity values in the adjacency matrix. We examined the global efficiency and clustering coefficient changes in different frequency bands relative to various density values and found the value which maximized the difference between measures corresponding to 2-back and rest by Wilcoxon signed rank non-parametric test. Finally, the edge density value was selected to be 0.6. We preserved the values of the adjacency matrix at or above the 60 percentile and discard the others. For instance, Fig. 1. illustrates Global efficiency changes in theta band based on different density values. This figure represents the robustness of the calculated adjacency matrix to variations in density values.

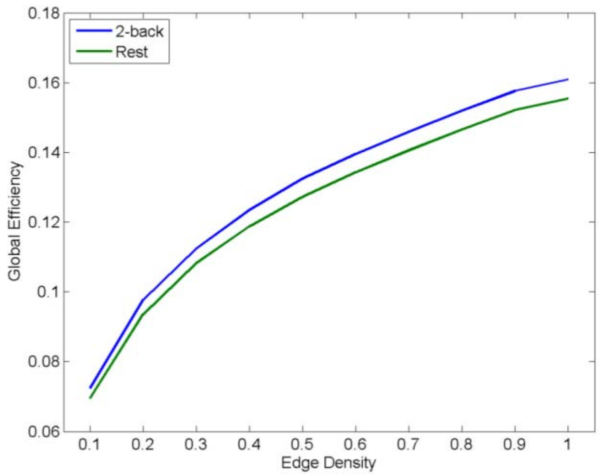

Figure 1. Global efficiency as a function of edge density

III. RESULTS

Fig. 2. represents the values of network's parameters, namely global efficiency and clustering coefficient, in working memory and rest conditions for four frequency bands. WM1 refers to the first part of 2-back task in each trial, which is mostly associated with execution and manipulation of information, and WM2 belongs to the last 1100ms of 2-back trials, commonly contributed to the maintenance of information. Statistical analysis was performed using Wilcoxon signed rank non-parametric test in order to compare each pair of network measures. In other words, for each frequency and measure, we have assessed the existence of a meaningful difference between WM1 and WM2, WM2 and rest, and WM1 and rest conditions.

In the Gamma band, we did not find any significant changes between states neither for global efficiency nor for clustering coefficient. Global efficiency and clustering coefficient in the theta band was significantly larger for the WM1 condition in comparison with the rest state. In contrast, these parameters were higher in the alpha and beta bands for rest condition compared to WM1 (Fig. 2).

Theta synchronization between different brain areas plays an important role in the mechanisms of working memory and long-term memory [12]. There is a distinct alteration in the theta phase synchronization during execution, manipulation and maintenance parts of working memory [12]. Although, it is difficult to thoroughly separate these cognitive processes in the N-back task, it is roughly acceptable that manipulation and execution are more dominant in the first part of each trial (WM1) while maintenance is mostly present in the second part (WM2). Our result demonstrated more local and global synchronization in WM1 and WM2 in comparison to resting states, which is completely in agreement with the previous studies [13]-[15]. Moreover, we showed that theta coupling was relatively higher for WM1 compared to WM2.

In the alpha band, global efficiency and clustering coefficient were significantly larger for WM2 in comparison with rest state. This increase which presents more synchrony between both near and far brain regions is consistent with cortical idling or active inhibition theory, stating that alpha synchronization in a retention period of working memory is higher than a rest condition [16]. The reduced global and local integration of WM1 in the alpha band may be expressed by the widespread view that cortical activation, most prominent in WM1, is associated with alpha event related desynchronization [17].

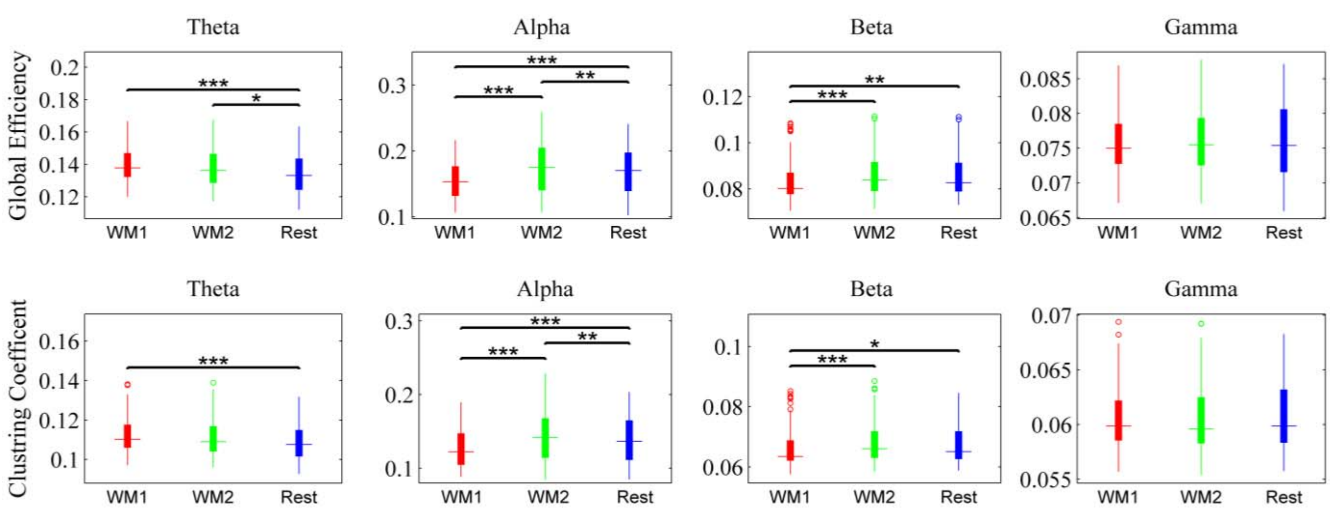

Figure 2. Global efficiency and clustering coefficient in four frequency bands and three cognitive states. One asterisk refers to $p<0.05$, two represent $p<0.01$, and three display $p<0.001$.

Some studies suggests an increase in the beta phase synchrony during maintenance of information in working memory in comparison with the rest state [12]. Our findings exhibited an increment in this parameter for WM2, although it is not statistically significant. The reason for this insignificance may be the fact that low number of items had to be maintained in our tasks, hence not providing a high memory load for participants.

IV. Conclusion and Discussion

In this study we assessed functional brain networks, constructed using the phase synchrony index, during a working memory task and rest condition, utilizing graph measures defined for brain networks. The obtained results showed different patterns among the four frequency bands. The outcomes are in agreement with the most researches of working memory. The results generally suggest that, like the brain oscillations, different processes are involved in synchronization between brain areas in a wide range of frequency bands.

Two recent works have investigated the network parameters related to the N-back task to assess the effect of working memory load on brain networks [18], [19]. The MEG study revealed that with increasing the task difficulty, functional brain networks tend to move toward random networks, with higher global efficiency and lower clustering coefficient [18]. In contrast, the fMRI research did not represent a significant change between four conditions of N-back task, for the corresponding graph parameters [19]. Nevertheless it was stated that, brain networks become more random and their connectivity decrease as the task gets more difficult [19]. In the current study, we did not compare different working memory conditions, but we evaluated network changes from a resting state to working memory usage. Our results delineated that the small-world property of brain networks in theta band strengthens by involvement in the 2-back task, in both WM1 and WM2. This may be because of a stronger connectivity between near and far brain regions in the WM conditions in comparison to the resting state. These connectivity patterns mainly include frontal and parietal regions which are the substantial areas in memory processes. These associations has widely asserted in working memory literature, using coherence analysis [15] and multivariate autoregressive modeling [6], [20].

Although the difference in network parameters between WM and rest conditions may be predictable, the distinctive patterns of connectivity between two WM parts is of particular importance. This difference illustrates that brain networks are in a critical state [18], suggesting that their characteristics and topology can change in less than one second. This issue may correspond to the economy of brain networks [21]. The mentioned characteristic points out that brain network is an economical system, and there is a trade-off between minimizing wiring-cost and allowing short and long connectivity between brain regions. With this in mind, as the difference is conspicuous in our results, brain graphs reorganize based on this trade off in time scales in range of millisecond, so to be cost and performance efficient. This observation motivates the researchers to contemplate the dynamics of brain networks in their future works.

Another interesting behavior of brain networks, which has been demonstrated in the result section, is their frequency dependent demeanor. It indicates that neuronal oscillations in a wide frequency range are responsible for different cognitive processes. For instance, our result may support this hypothesis that beta oscillations are more involved in maintenance part of working memory rather than execution period. However, such results cannot be admitted at this time and must be evaluated comprehensively in future studies.

Albeit in this paper we mentioned some previous studies of working memory, it is very difficult to compare the results of this study with previous publications. Many factors like the nature of study (e.g. EEG, MEG), the approach of data analysis, and number of graph nodes have an indisputable effect on the final results. Also, to the best of our knowledge, very few studies have focused on the graph measures of functional brain networks during N-back task using EEG signals in healthy people. With this in mind, a wide range of researches with different techniques are needed for better comprehension of the network perspective of working memory.

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