Analysis of a phase synchronized functional network based on the rhythm of brain activities*

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Rhythm of brain activities represents oscillations of postsynaptic potentials in neocortex, therefore it can serve as an indicator of the brain activity state. In order to check the connectivity of brain rhythm, this paper develops a new method of constructing functional network based on phase synchronization. Electroencephalogram (EEG) data were collected while subjects looking at a green cross in two states, performing an attention task and relaxing with eyes-open. The EEG from these two states was filtered by three band-pass filters to obtain signals of theta (4–7 Hz), alpha (8–13 Hz) and beta (14–30 Hz) bands. Mean resultant length was used to estimate strength of phase synchronization in three bands to construct networks of both states, and mean degree K and cluster coefficient C of networks were calculated as a function of threshold. The result shows higher cluster coefficient in the attention state than in the eyes-open state in all three bands, suggesting that cluster coefficient reflects brain state. In addition, an obvious fronto-parietal network is found in the attention state, which is a well-known attention network. These results indicate that attention modulates the fronto-parietal connectivity in different modes as compared with the eyes-open state. Taken together this method is an objective and important tool to study the properties of neural networks of brain rhythm.

Keywords: electroencephalogram, phase synchronization, rhythm, functional brain network

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1. Introduction

Electroencephalogram (EEG) is the recording of electrical activity along the scalp and reflects the firing of neurons within the cerebral cortex. The features of EEG has been analysed by various methods in time and frequency domains over the last few years, such as fast Fourier transform, wavelet transform, and non-linear dynamic analysis.[1−4] Human alpha (8–13 Hz) rhythms are dominant roughly in 95% of normal adults over posterior regions in resting eyes-closed (EC) state,[5] and global alpha rhythms are suppressed from the eyes-closed (EC) to eyes-open (EO) or attention state.[6,7] This state change is described as earlier 'alpha-block' [8] or modern 'alpha desynchronization'.[9,10] Although the underlying mechanisms remain unclear, alpha desynchronization to visual input has been proposed to reflect long-range communication between cortical and thalamo-cortical areas, to facilitate visual perception or information processing.[11,12] Except alpha band, theta (4–7 Hz) and beta (14–30 Hz) bands also show the reduction of power from EC to EO state.[7]

Recently more studies focus on the functional connectivity among brain activities of different brain areas, which is assumed as a tentative index of functional interactions.[13] Stam *et al.* have investigated the difference of functional brain networks in Alzheimer's disease (AD) patients and healthy control subjects in resting state.[14] Graph theoretical analysis was applied to the beta band EEG, and a loss of small-world network characteristics was found in AD patients. In EEG network, each recorded electrode represents a vertex of graph, and strong correlativity between two channels constructs an edge. Correlation coefficient, synchronization likelihood, and detrended fluctuation analysis between all pairwise combinations of EEG channels were applied to estimating the correlativity and converted to graphs by a threshold.[15−17]

Complete synchronization of oscillators may be caused by the sufficiently strong coupling between two oscillators.[18] Subsequent research has led to the discovery of phase synchronization phenomenon which becomes very important for the investigation of neuronal interactions.[19] Phase synchronization means that their phases are adjusted by a small coupling of oscillators, but amplitudes remain chaotic and un-

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correlated. In the present study, we develop a new method of constructing phase synchronization network based on the parameter of mean resultant length (MRL).

2. Theory and methods

2.1. EEG recordings and preprocessing

Eleven healthy right-handed volunteers (six males and five females, mean age 21.6 years, standard deviation (SD) 0.8, range 20–23) from the university participated in this experiment. Subjects had no physical/psychological problem or were not using any medication. Each subject signed an informed consent before EEG recording, and they were compensated after testing.

Experiment includes two sessions: EO resting state for three minutes, and a classical visual attention task for about ten minutes (half time for attention to right visual field). In EO state, subjects were required to keep the EO with fully relaxed with stable binocular fixation on a central green cross but no instruction. In the visual attention task,[20] trials began with a 300–500 ms central green cross, after which subjects were presented with a circular black and white checkerboard with a randomly selected visual field and size for 50 ms. Subjects were asked to focus on one visual field per block, and respond to the infrequent small checkerboards at the attended visual field using a keyboard as quick as possible. Due to the very short intervals between successive stimulus onsets and difficulty of target discrimination, subjects needed to pay enough attention to maintain good performance. Stimuli include 80% standard stimuli and 20% target stimuli. Fifty percent of the standard stimuli were presented on the unattended side, which were regarded as unattentional state. Hence, only 40% data were analysed in present study.

The EEG was recorded from 128 channels using a modified 10–20 montage system (electrical geodesics inc (EGI) system) and the reference electrode was the Cz, (129th) electrode. The EEG was digitized at a rate of 500 Hz with an amplifier band-pass of 0.1–48 Hz, and was preprocessed off-line.

In attention task, EEG data were segmented from 200 ms before the onset of the central green cross to 300 ms after the cross onset (0.5 s for an epoch). Hence, in the EO state, the length of epoch was 0.5 s as well. The visual stimuli of two states were the same. After segmenting, EEG data were filtered by a 1–31 Hz band-pass filter, referenced to the average reference. Significant artifacts (head movements, eye movements, skin artifacts, muscle activity) were excluded by automatic artifact rejection (epochs with any point more than 100 μV). At last, 2277 epochs remained for EO state, 3727 epochs remained for attention state, which were used for the further analysis.

Each epoch of EO and attention states of every subject was filtered by three band-pass digital elliptic filters to obtain the signals of theta (4–7 Hz), alpha (8–13 Hz) and beta (14–30 Hz) bands. The data from the green cross onset to 300 ms after its onset (0.3 s for an epoch) were used to extract the brain functional network.

2.2. Computation of the index of phase synchronization R

Correlations between all pair-wise combinations of EEG channels were computed with the MRL, which is a much more straightforward method for estimating phase synchronization strength. The MRL has been used as a measure of bivariate phase synchronization in a number of EEG data studies.[21] In the present study, each epoch data is a matrix of 129×151, in which each channel is considered to be an oscillator ($N = 1, 2, \ldots, 129$) and points ($k = 1, 2, \ldots, 151$) represent temporal course. Instantaneous phase $\phi(t)$ to the time series $x(t)$ of oscillator i is estimated by Hilbert transform H as

$$\phi(t) = \arg[x(t) + \mathrm{i}\mathrm{H}x(t)]. \tag{1}$$

Therefore the instantaneous phase difference between oscillators i and j is defined as

$$\Delta\phi_{ij}(k) = \phi_j(k) - \phi_i(k), \tag{2}$$

which is a random variable characterized by a probability distribution. Hence, the strength of synchronization between each two oscillators i and j can be quantified as

$$R_{ij} = \left| \frac{1}{n} \sum_{k=1}^{n} \exp(\mathrm{i}\Delta\phi_{ij}(k)) \right|. \tag{3}$$

If points on the unit circle are assigned to the values of the phase difference $\Delta\phi_{ij}(k)$ in a sample, R_{ij} can be visualized as the distance between the centre of gravity of the points and the original point. The R_{ij} takes on values in the range from 0 to 1, describing a continuum between no and perfect phase synchronization. Weak synchronization corresponds to a

nearly uniform distribution of the phase difference on the unit circle, and strong synchronization means a distribution concentrated on one side.

The result of computing the MRL for all pair-wise combinations of channels is a square 129×129 matrix. The MRL matrices of each epoch data were calculated and then averaged to a mean matrix $\boldsymbol{R}$. Therefore, 66 phase synchronization matrices $\boldsymbol{R}$ with two states (EO and attention) of 11 subjects in three bands were obtained.

2.3. Computation of the mean degree K and cluster coefficient C

Phase synchronization matrices $\boldsymbol{R}$ can be converted to the different graph with different threshold T. However, there is no unique way to choose T. A whole range of values of T (0–1) were explored in the present data, and different values of T were found in three bands. For the theta band, values of T were picked as 0.86–0.96, with increments of 0.01. For the alpha band, values of T were picked as 0.6–0.95, with increments of 0.05. For the beta band, values of T were picked as 0.3–0.8, with increments of 0.1. If R_{ij} exceeds values of T, an edge exists between vertexes i and j. Finally, vertexes and edges construct a brain functional network.

For vertex i, if there are k_i other vertexes connecting with it, the degree of i is k_i. And the mean degree K of 129 vertexes is

$$K = \frac{\sum_{i=1}^{129} k_i}{129}. \tag{4}$$

If there are k_i other vertexes connecting with vertex i, number of maximum edges between these k_i vertexes is $k_i(k_i-1)/2$. In fact, there are only E_i edges among k_i vertexes. The cluster coefficient of vertex i is

$$C_i = \frac{2E_i}{k_i(k_i-1)}. \tag{5}$$

Hence, the cluster coefficient of brain functional network is

$$C = \frac{\sum_{i=1}^{129} C_i}{129}. \tag{6}$$

2.4. Statistical analysis

Pair-wise t-tests and linear regression of the plots of K and C as a function of threshold were applied. In all tests, $P < 0.05$ was accepted as significant, where P is the probability value of a statistical hypothesis test. The statistical toolbox in Matlab was used for statistical procedures in the present study.

3. Results

3.1. Theta band network

Global mean theta-band phase synchronization is higher in EO state [0.8853 for EO, 0.8795 for attention, $t(10) = 4.75$, $P = 0.0008$]. Figure 1 shows the mean degree K and cluster coefficient C of 11 subjects as a function of threshold T for two states.

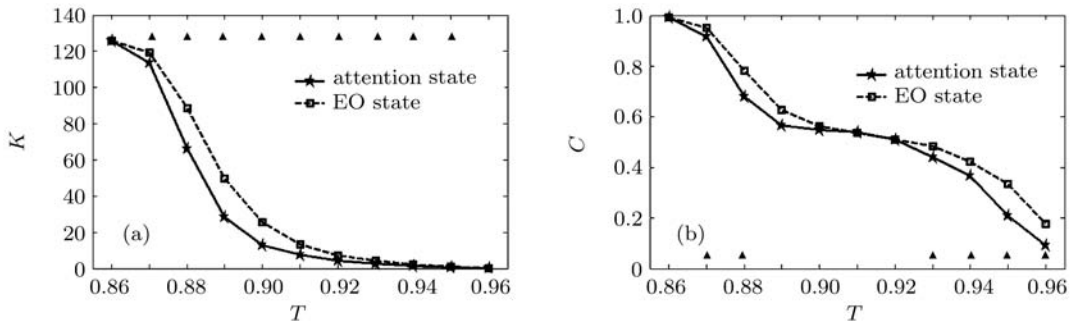


Fig. 1. Mean degree K and cluster coefficient C for attention and eyes-open states in theta band (black triangles indicate significant difference between attention and eyes-open state): (a) mean degree K as a function of threshold T, (b) mean cluster coefficient C as a function of threshold T.

With a threshold of 0.86, the corresponding graphs are almost fully connected with edges among almost all vertices yielding a corresponding K close to 128 and C close to 1. With increasing threshold, mean degree K and cluster coefficient C starts to decrease. With the threshold of 0.96, most edges lost connection so that the corresponding K and C are close to zero. The K of the EO state is significantly higher than K

of the attention state in almost all thresholds except the smallest and biggest value of T ($P < 0.05$). The C of the EO state is also significantly higher than that of the attention state in thresholds of 0.87, 0.88, 0.93, 0.94, 0.95, and 0.96 ($P < 0.05$).

Figure 1 shows that there are no differences in C for the middle values of T, but there are less connected edges for the attention state in the corresponding T. The results of C might be influenced by differences in mean degree K for a given value of T. Hence the values of C of the same mean degree K ($K = 4, 7$) were compared between two states. Furthermore, corresponding random networks were generated for comparing C with both states. Figure 2 shows the cluster coefficient C for attention, EO states, and random network for the same degree K. Error lines represent the SD.

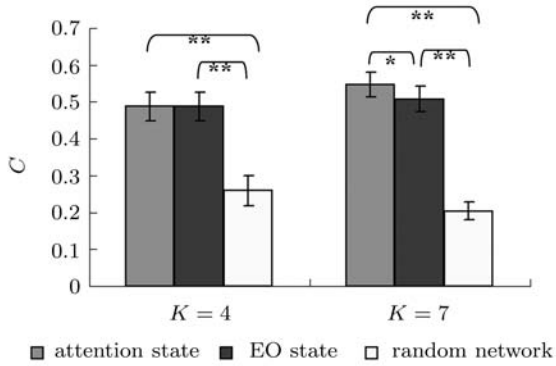


Fig. 2. Cluster coefficient C for the same degree K in three conditions in theta band. Significant results are designated as follows: $*$, $P < 0.05$; $**$, $P < 0.01$.

Cluster coefficient C of both states is significantly higher than that of random networks when K is 4 and 7 ($P < 0.001$). For $K = 7$, C of attention state is significantly higher than that of EO state [$t(10) = 3.30$, $P = 0.008$]. As expected, C increases with K in both states [$t(10) = 6.59$, $P = 0.0001$ for attention state; $t(10) = 2.55$, $P = 0.03$ for EO state].

Figure 3 shows the mean graphs with the positions of the recording electrodes in both states when $K = 5$. The C of attention state is slightly higher than that of EO state. Compared with the EO state, graph of the attention state has a larger number of edges between the central frontal and parietal areas.

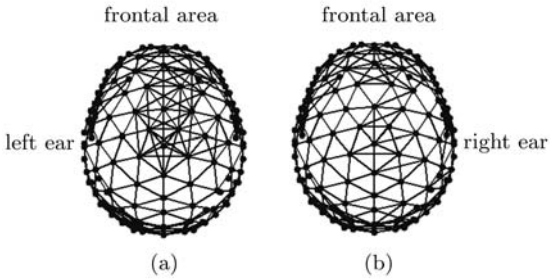


Fig. 3. Graphs of the attention, eyes-open states in theta band. (a) attention state, $C = 0.4749$; (b) eyes-open state, $C = 0.4636$.

3.2. Alpha band network

Global mean alpha-band phase synchronization is higher in EO state [0.7082 for EO, 0.6729 for attention, $t(10) = 6.91$, $P < 0.0001$]. Figure 4 shows the mean degree K and cluster coefficient C of 11 subjects as a function of threshold T for two states. The results of Fig. 4 are similar to those of Fig. 1. With increasing threshold, mean degree K and cluster coefficient C start to decrease. The K of the EO state is significantly higher than K of the attention state in almost all thresholds except smallest value of T ($P < 0.05$). The C of the EO state is also significantly higher than C of the attention state in thresholds of 0.65, 0.70, 0.75, 0.85, 0.90, and 0.95 ($P < 0.05$).

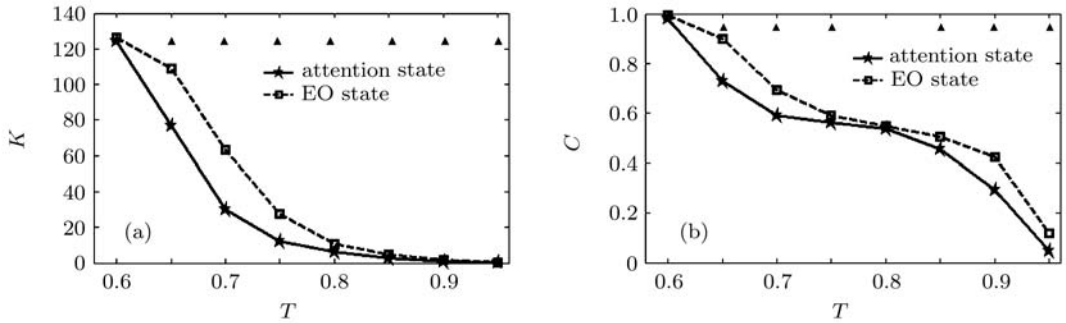


Fig. 4. Mean degree K and cluster coefficient C for attention and eyes-open states in alpha band (black triangles indicate significant difference between attention and eyes-open state): (a) mean degree K as a function of threshold T, (b) mean cluster coefficient C as a function of threshold T.

The values of C of the same mean degree K ($K = 7, 10$) were compared between two states too (see Fig. 5). Similarly, cluster coefficient C of both states is significantly higher than that of random networks when K is 7 and 10 ($P < 0.001$). The C increases with K in both states [$t(10) = 2.44$, $P = 0.035$ for attention state; $t(10) = 2.41$, $P = 0.037$ for EO state]. For $K = 10$, C of attention state is significantly higher than that of EO state [$t(10) = 2.42$, $P = 0.036$].

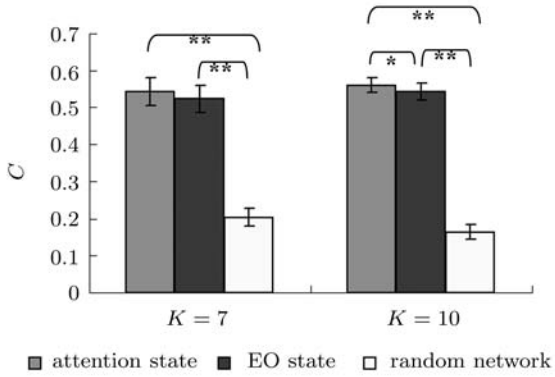


Fig. 5. Cluster coefficient C for the same degree K in three conditions in alpha band. Significant results are designated as follows: $*$, $P < 0.05$; $**$, $P < 0.01$.

Figure 6 shows mean graphs with the positions of the recording electrodes in both states when K is 5. The C of attention state is slightly higher than that of EO state. Compared with the EO state, graph of the attention state has a larger number of edges between the frontal and vertical areas.

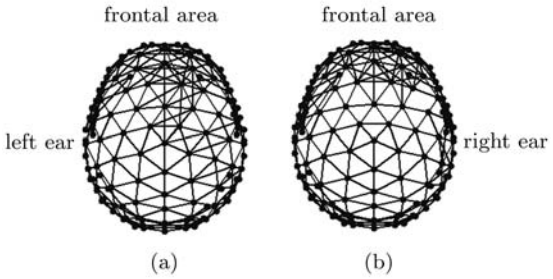


Fig. 6. Graphs of the attention and eyes-open states in alpha band. (a) attention state, $C = 0.4819$; (b) eyes-open state, $C = 0.4695$.

3.3. Beta band network

Global mean beta-band phase synchronization is higher in the EO state [0.4119 for EO, 0.3801 for attention, $t(10) = 6.71$, $P = 0.0001$]. Figure 7 shows the mean degree K and cluster coefficient C of 11 subjects as a function of threshold T for two states. Mean degree K and cluster coefficient C decrease with increasing threshold. The K of the EO state is significantly higher than K of the attention state in all thresholds ($P < 0.05$). The C of the EO state is significantly higher than C of the attention state when thresholds are 0.3, 0.6 and 0.8 ($P < 0.05$). Different from theta and alpha bands, C of the EO state is significantly lower than C of the attention state when the value of T is 0.5 [0.5690 for EO, 0.5885 for attention, $t(10) = 3.55$, $P = 0.005$].

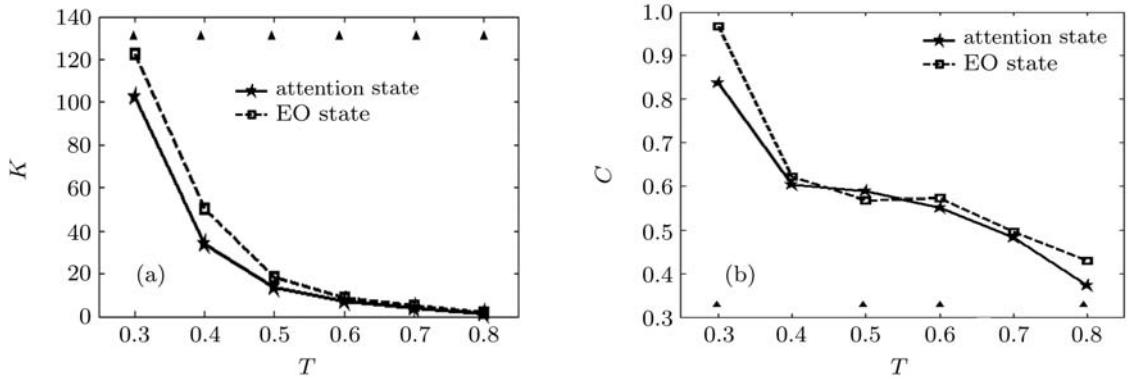


Fig. 7. Mean degree K and cluster coefficient C for attention and eyes-open states in beta band (black triangles indicate significant difference between attention and eyes-open state): (a) mean degree K as a function of threshold T, (b) mean cluster coefficient C as a function of threshold T.

The values of C of the same mean degree K ($K = 10$, 15) were compared between two states too (see Fig. 8). Similarly, cluster coefficient C of both states is significantly higher than that of random networks when K is 10 and 15 ($P < 0.001$). The C does not increase with K in both states and random network. For $K = 10$, there is no significant difference of C between two states. But when K is 15, C of attention state is significantly higher than that of EO state [$t(10) = 3.6$, $P = 0.005$].

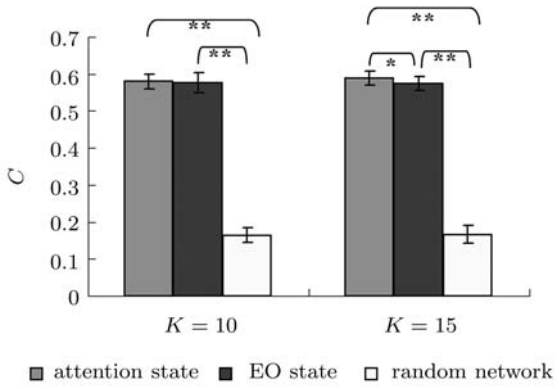


Fig. 8. Cluster coefficient C for the same degree K in three conditions in beta band. Significant results are designated as follows: $*$, $P < 0.05$; $**$, $P < 0.01$.

Figure 9 shows mean graphs with the positions of the recording electrodes in both states when K is 5. The C of attention state is lower than that of EO state. Compared with the EO state, graph of the attention state has a larger number of edges between the frontal, parietal, and right temporal areas.

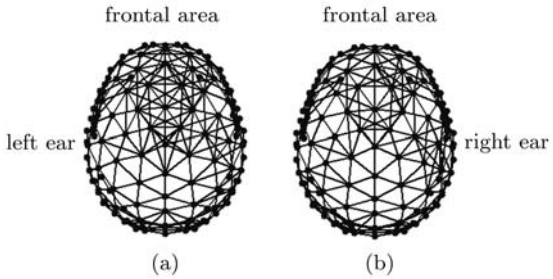


Fig. 9. Graphs of the attention and eyes-open states in beta band. (a) attention state, $C = 0.4505$; (b) eyes-open state, $C = 0.4725$.

4. Discussion

Mean values of phase synchronization in three bands are higher for EO resting state than those of attention state, indicating that attention decreases the phase synchronization of whole 4–30 Hz. In both states synchronization of beta band is the lowest level. These results are consistent with the results of the mean degree K and cluster coefficient C of the graphs for three bands. For a whole range of threshold values, the K and C mostly show higher values in EO state (Figs. 1, 4 and 7), implying that the local connectedness of networks in attention is relatively spared. The sparing of the C in attention means that if a channel is strongly correlated to the other two channels, then the likelihood that the other two channels will also be strongly coupled is significantly lower than in EO state.

For a given threshold, graphs of EO state have more edges, and this will result in a higher C. The analysis by computing C with the same K shows that attention has a significantly higher C compared with EO state in specifically mean degree K with different bands (Figs. 2, 5 and 8). Thus, the higher C in attention state with the same edges reflects a true difference in the organization of functional networks from EO state. In theta, alpha and beta bands, the fronto-parietal phase coupling is stronger for attention than that of EO state (Figs. 3, 6 and 9). The finding of theta band is in agreement with the previous attention studies, implying that prefrontal brain areas may control the activation level of the visual cortex in a top-down manner.[22] Synchronization of a beta band oscillatory network was observed between the right cingulum, right posterior parietal lobe, and left frontal areas,[23,24] which is also presented in our data (Fig. 9). This suggests that this beta synchronization constructs a functional network that implements attentional preparation, or readiness. The beta activities, at least under certain conditions, may also be sensitive to various cognitive activities requiring attention or memory. The C is much higher than that of a random graph, implying the small-world properties in EEG data. The present study provides further evidence for the presence of small-world features in human functional brain networks.[25−27]

The principal finding of the present study is that C in attention state of three bands is higher than that in EO state, and there is an obvious fronto-parietal network in attention state. Cluster coefficient may reflect the degree of fixing attention. The stronger attention is, the higher C is. Alpha and other rhythms recorded from scalp EEG are thought to represent oscillations of postsynaptic potentials in neocortex, one or more of which might be an indicator of the brain state.[5] Previous studies searching for theta, alpha and beta rhythms generators have consistently identified the contribution of the parietal and frontal cortices network,[28,29] which is known to support attentional processes.[30]

5. Conclusion

In conclusion, we have developed a method of constructing functional brain network by using the MRL matrices and explored the difference of phase synchronized functional brain network between the resting EO

and attention states. The result showed higher cluster coefficient in the attention state than in the EO state in all three bands, suggesting that cluster coefficient reflects brain state. We found that attention task modulated the parietal-frontal network activities in different modes compared with EO state due to attention processing. Taken together, the results indicate that the features of phase synchronized functional brain network correlate with human brain state. The present method is capable of studying the properties of neural networks of brain rhythm. In future work, we will apply this method in various fields of cognitive and clinical neuroscience.

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