The occupational brain plasticity study using dynamic functional connectivity between multi-networks: take seafarers for example

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**ABSTRACT** The exploration of brain plasticity through functional magnetic resonance imaging (fMRI) technology is a hot topic in the field of brain science research. In order to explore the specificity of the brain functional networks of seafarers and the influence of marine environment on seafarer brain functional networks, in this paper, nine resting-state brain functional networks of seafarers were studied by using group independent component analysis with intrinsic reference method based on the full use of fMRI priori information, and the static and dynamic functional connections between these brain networks were statistically analyzed. The results showed that there was a significant difference between seafarers and non-seafarers in the dynamic functional connectivity of individual subjects. Furthermore, the dynamic functional connection patterns between the two groups of subjects corresponding to the nine brain networks were extracted by using the sliding time window and clustering methods. It was found through analysis that the brain functional networks underwent specific functional recombination and transformation during the process of brain activity, and showed dynamic functional connectivity states which were significantly different from those of non-seafarers. The research results have important reference value for revealing the specificity of the brain function neural activity of seafarer population and the brain plasticity of seafarer occupation.

**INDEX TERMS** fMRI, dynamic functional connectivity analysis, sliding window correlation analysis, clustering, seafarer.

**I. INTRODUCTION**

It is known to all that the working conditions of seafarers on the sea have large differences compared with the terrestrial environment, which makes the seafarers vulnerable to the natural and working environments as well as many other complex factors, and leads to the functional connectivity (FC) changes of seafarers' brain [1, 2]. These changes not only influence the physical and psychological health of seafarers themselves, but also seriously affect the safety of navigation operation. Therefore, it is very important to explore the influence of maritime environment on seafarers' brain [3, 4]. As a newly emerging neuroimaging technology, functional magnetic resonance imaging (fMRI) has many unique advantages compared with other imaging technologies, and it has been widely used in various fields of brain research. For example, Shi et al. proposed a kind of seafarers psychological health assessment method based on the fMRI technology, which caused the extensive concern of the shipping industry [5]. Wang et al. used the sample entropy to explore the functional complexity of seafarers’ brain, and the results showed that the seafarer occupation indeed impacted the brain’s complexity [6].

The FC analysis based on resting-state fMRI has been widely used to study the neural mechanism and diagnosis of mental diseases [7, 8]. The traditional brain network analysis method generally assumes that the brain functional network model has the temporal invariance, thus a static and invariant brain network is constructed by using the whole time series, where the FC is measured over the entire scan [9-11]. This assumption has been widely used in many studies, because it provides a simple and convenient framework for us to examine large-scale brain networks and explore the correlation between functional and structural connectivity [12, 13]. However, the time series in fMRI are often non-
stationary, which makes it difficult to guarantee the premise of the temporal invariance in the process of brain network construction. On the contrary, the dynamic FC (DFC) shows a good performance in revealing the complex and changeable characteristics and mechanism of the brain network. Therefore, we should consider the time-varying characteristics when building the human brain network model, and construct a dynamic brain network to better mine the hidden information of the human brain network [14-16].

More and more studies have suggested that the brain’s functional connectome under resting or task conditions is not static, but undergo dynamic integration and coordination on multiple time scales, and showing complex spatiotemporal dynamic responses to internal and external stimuli [17-19]. DFC analysis is generally divided into two methods. One is using the average time series corresponding to each brain region of existing anatomical templates such as Anatomical Automatic Labeling (AAL), to calculate the DFC between different brain regions [20, 21]. The other is using the data-driven methods such as independent component analysis (ICA), to obtain the corresponding brain functional network and its corresponding time series in fMRI data, so as to build a DFC network between different networks [22, 23].

For example, Allen et al. described an approach to assess whole-brain FC dynamics based on spatial independent component analysis, sliding time window correlation, and k-means clustering of windowed correlation matrices, and applied it for the study of a large sample of young adults which suggested that the time varying aspects of FC can unveiled flexibility in the functional coordination between different neural systems [24]. Shen et al. investigated how the dynamics of resting-state FC were linked to driving behavior by comparing 20 licensed taxi drivers with 20 healthy non-drivers using a sliding window approach [25]. Shi et al. investigated DFC among large-scale brain networks during resting state fMRI in relation to subjective well-being (SWB) in two large independent datasets, and found that the dynamic interaction between networks involved in self-reflection, emotional regulation, and cognitive control underlies SWB [26].

Recently, Wang et al. used a dynamic functional connectome characterization model with the automatic target generation process k-means clustering to explore the functional reorganization property of resting brain states, driven by long-term career experience, and taken sailors as an example. The results revealed the specifically functional alterations modulated by sailing experience and particularly provided the evidence that functional plasticity was beneficial in reorganizing brain’s functional topology, which could be driven by career experience [27]. However, the current research mainly focuses on the analysis of DFC of a single network, and there are no studies to consider the dynamic changes and development rules between the intrinsic brain functional networks in seafarers' brain.

In this paper, the specificity of the brain function network of seafarer population and the influence of marine environment on seafarers’ brain functional networks were studied through the analysis of the DFC between multifunctional networks. In the process of studying brain functional networks by using fMRI technology, the brain functional connectivity detection is the most important step. Only the more accurate spatial networks are detected, the better results can be obtained in the various subsequent application researches by using these networks. Therefore, we adopted the group ICA with intrinsic priori information to obtain more accurate brain functional networks in our study [28]. Then, the DFCs between these networks are calculated by using the sliding window method at the group level and single-subject level. Finally, cluster analysis is used to extract the specific patterns implicit in these DFCs and analyze the state transition characteristics between these patterns. The research results have important reference value for revealing the specificity of the brain function neural activity of seafarer population and the brain plasticity of seafarer occupation.

The remainder of this paper is organized as follows: the relevant materials will first be presented followed by the acquisition of brain functional networks, which are obtained for the functional connectivity analysis. Finally, the results and analysis will be presented together with interpretations and conclusions related to the potential significance and limitations of this study.

II. MATERIALS AND METHODS

A. DATA COLLECTION

In this study, 88 seafarers that participated in the experiment came from a shipping company of Shanghai, and obtained the resting-state fMRI data before sailing. Before the data acquisition, all the participants were informed about the purpose of this study and given the written informed consent in accordance with the Declaration of Helsinki. In the process of data acquisition, all the participants were instructed to keep the body motionless, eyes closed, relaxed (don’t think anything systematically) and awake; their ears were stuffed up with the earplugs in order to reduce effect of the machine noise.

The fMRI data of seafarers were acquired in the Shanghai Key Laboratory of Magnetic Resonance of the East China Normal University. The fMRI dataset was acquired on a Siemens 3.0 T scanner using a gradient echo planar imaging with 36 slices of whole-brain coverage and 160 volumes, a TR of 2.0s and a scan resolution of 64x64. The in-plane resolution was 3.75x3.75mm2, and the slice thickness was 4 mm.

The resting-state fMRI data of 100 healthy subjects were downloading from the public neuroimaging database (http://www.nitrc.org/projects/fcon1000/), which was used as the non-seafarers control group for the purpose of
comparison. The image dataset was acquired using single-shot SENSE gradient echo EPI with 33 slices, providing whole-brain coverage and 225 volumes, a TR of 2s, an TE of 30ms, a FA of 80 and a scan resolution of 64×64. The in-plane resolution was 3.13 mm×3.13 mm, and the slice thickness was 3.6 mm.

**B. PREPROCESSING OF fMRI DATA**

In the experiment, all of the fMRI data were preprocessed by using the DPARSF software (http://rfmri.org/DPARSF), and the preprocessing steps included removing the first 10 time points, slice timing, motion correction, spatial normalization and spatial smoothing with the Gaussian kernel set to 4 mm. In particular, ICA was implemented with FastICA algorithm [29] which was performed by using the GIFT software (v2.0e) (http://mialab.mrn.org/software/). Moreover, ICASSO [30] with 20 runs of ICA was used to obtain reliable ICs, and minimum description length (MDL) [31] was used to estimate the number of ICs. Furthermore, the location and display of these networks were assessed by using the MRicro software (http://www.mricro.com).

**C. BRAIN FUNCTIONAL NETWORKS ACQUISITION**

In this study, group ICA (GICA) with intrinsic prior information (GICA-IR) method was firstly used to obtain the temporal and spatial functional components at the group level, and then the spatial and temporal functional components corresponding to each subject in the group was obtained by dual-regression. Particularly, the calculation process of the GICA-IR method is shown as follows:

Assuming that there are a total of K subjects in the group, and all subjects have T time points and V voxels after normalization. First, we implement ICA on each subject of the group. For subject i, ICA can be defined as:

$$X_i = M_i S_i (i = 1, 2, L , K)$$

(1)

where $X_i$ is an $T×V$ fMRI observed data, $S_i = (s_{i1}, s_{i2}, L , s_{iN_i})^T$ is a $N_i×V$ matrix, and each row of $S_i$ represents an independent component (IC) of subject i. $M_i = (m_{i1}, m_{i2}, L , m_{iN_i})$ is a $T×N_i$ mixing matrix, and each column of $M_i$ represents the corresponding time course of the IC in $S_i$. $N_i$ denotes the number of ICs for subject i.

Next, we denote $s_{i}^{n_i} (i = 1, 2, L , K)$ as the $n_i (1 ≤ n_i ≤ N_i)$ th IC, which is the interest IC of size $V×1$ for subject i. The correspondence of the ICs across different subjects corresponding to the group IC (GIC) can be measured using the absolute value of the spatial correlation. Now we use principal component analysis to calculate the spatial priori information from the $K×V$ matrix $R$ which consists of all $s_{i}^{n_i} (i = 1, 2, L , K)$:

$$R = [s_{11}^{n_1}, s_{21}^{n_2}, L , s_{K}^{n_k}]$$

(2)

Then, the eigenvalues $\lambda_k (k = 1, 2, L , K)$ such that $0 ≤ \lambda_1 ≤ \lambda_2 ≤ \lambda_k$, and the corresponding eigenvectors $e_k (k = 1, 2, L , K)$ of covariance matrix $C = E[R R^T]$ can be calculated, where $e_k$ is a column vector of size $K×1$. Finally, we select the first principal component as the spatial priori information $r$:

$$r = e_k R$$

(3)

where $r$ is a row vector of size $1×V$ and the corresponding contribution of $r$ can be calculated by $c_r = \lambda_1 / \sum_{k=1}^{K} \lambda_k$.

Thirdly, the spatial priori information $r$ is used as the intrinsic reference signal in the GICA for the group data analysis. The GICA can be defined as:

$$(X_1; X_2; L ; X_K) = MS$$

(4)

where $M$ is a $KT×V$ group mixing matrix, $S$ is an $N×V$ matrix in which each row represents a GIC, and $N$ denotes the number of GICs. The solving of (4) can be modeled as a constrained optimization problem as follows:

$$\text{Maximize } J(s) = [E[G(s)] - E[G(v)]]^2$$

Subject to $g(s) = \varepsilon(s, r) - \xi ≤ 0$

$$h(s) = E[s^2] - 1 = 0$$

(5)

where $s$ is the output signal, $J(s)$ is the contrast function used to measure the independence of $s$, $G(·)$ is a non-quadratic function, and $v$ is a Gaussian random variable. $r$ is the reference signal, $\varepsilon(s, r)$ is a distance criterion, and $\xi$ is a threshold parameter which needs to limit the distance such that the desired output signal should be the only one satisfying the inequality constraint. The equality constraint $h(s)$ is used to compel the output signal have a unit covariance. Finally, the solution to equation (5) can be solved by FastICA algorithm [28], which is used to obtain the output signal.

**D. FUNCTIONAL CONNECTIVITY ANALYSIS**

In this section, we mainly analyzed the FCs among the brain functional networks obtained in section 2.3.1 between seafarers and non-seafarers at the group level and individual level, including static FC (SFC) and DFC. Firstly, SFC...
analysis was performed between the group brain functional components and the brain functional components of individual subjects in the group respectively, and the differences was tested by statistical analysis between seafarers and non-seafarers involved in the study, in which the differences at individual level were obtained by statistical testing of the average brain functional connections of each group.

![Image of brain functional networks](image)

**FIGURE 1.** The nine resting-state BFNs and their MNI coordinates including DMN, VIN, LVN, AUN, SMN, ECN, RWMN, LWMN and CCN for non-seafarers and seafarers at the group level, as shown in (A) and (B). The maps of these BFNs are obtained with threshold $|z| \geq 2$ after z-scored the ICs of GICA-IR.

Secondly, the sliding time window correlation method was used to analyze the DFCs between the brain networks at the group level and individual level, and the statistical difference between non-seafarers and seafarers was measured by the standard deviation across all DFCs. Then, affine propagation clustering (APC) algorithm was used to obtain the implicit brain functional connection patterns from the DFCs of all subjects, and a detailed analysis of the DFC patterns between non-seafarers and seafarers was conducted.

**III. RESULTS AND ANALYSIS**

In this section, we will compare and analyze the results of SFCs and DFCs between seafarers and non-seafarers at the group level and individual level respectively, so as to reveal the dynamic brain functional plasticity in seafarers.

**Figure 1** shows the nine classical resting-state brain functional networks (BFNs) and their Montreal Neurological Institute (MNI) coordinates at the group level, which obtained using GICA-IR method from the fMRI data of non-seafarers and seafarers, respectively. The nine BFNs include default mode network (DMN), visual network (VIN), lateral visual network (LVN), auditory network (AUN), sensorimotor network (SMN), executive control network (ECN), right working memory network (RWMN), left working memory network (LWMN) and cognitive control network (CCN). The spatial maps of these BFNs are obtained with threshold $|z| \geq 2$ after z-scored the ICs of GICA-IR.

**Figure 2** shows the results of SFCs and DFCs between the nine BFNs for non-seafarers and seafarers at the group level, where step 1 represents the calculation process of SFCs and the statistical results between non-seafarers and seafarers, and step 2 represents the calculation process of DFCs on the case that window width is 20 TRs. In order to evaluate the difference of DFCs between non-seafarers and seafarers, we calculate the standard deviations (SDs) of all DFCs on each pair of BFNs, and obtain the statistical results of SDs among the nine BFNs between non-seafarers and seafarers, as shown in step 3. According to the results of T-test with a confidence of 95% in the figure, we can find that these are no significant difference between non-seafarers and seafarers in the SFCs and SDs, respectively. This indicates that the variation among the nine BFNs between seafarers and non-seafarers cannot be reflected at the group level, either from the perspective of SFC or DFC. Therefore, we need to conduct more in-depth analysis from the individual level.

**Figure 3** shows the results of SFCs and DFCs between the nine BFNs for non-seafarers and seafarers at the individual level, where step 1 represents the calculation process of SFCs and the statistical results of mean SFC (MSFC) between non-seafarers and seafarers, and step 2 represents the calculation process of DFCs on the case that window width is 20 TRs for each non-seafarer and seafarer, respectively. Similar to the results in **Figure 2**, the SD of DFCs on each pair of BFNs is used to evaluate the difference of DFCs between non-seafarers and seafarers, so that we can calculate the SDs of DFCs among the nine BFNs for each non-seafarer and seafarer, and the statistical results between them are also obtained in step 3. It can be seen clearly from the figure that these is no obvious
difference between the MSFC of non-seafarers and that of seafarers according to the results of T-test with a confidence of 95%, but it has a significant difference between mean SD (MSD) of them. The results demonstrate that SFCs cannot reveal the difference among the nine BFNs between seafarers and non-seafarers, but DFCs may be provided a better way to study the changes among the nine BFNs of seafarers at the individual level.

FIGURE 2. The maps of SFCs between the nine BFNs of non-seafarers and seafarers and the T-test result between them at the group level, as well as the maps of DFCs between the nine BFNs of non-seafarers and seafarers and the T-test result between SDs of DFCs at the group level, where (A) represents non-seafarers and (B) represents seafarers. Note: # denotes that there is no significant difference according to T-test with a confidence level of 95%.
FIGURE 3. The maps of SFCs between the nine BFNs of non-seafarers and seafarers and the T-test result between their MSFC at and seafarer and the T-test result between MSD of DFCs at the individual level, where (A) represents non-seafarers and (B) represents seafarers. Note: # denotes that there is no significant difference and * denotes that there is a significant difference according to T-test with a confidence level of 95%.

Figure 4 shows the DFC states obtained by APC algorithm from the DFCs between the nine BFNs of all non-seafarers and seafarers at the individual level, as well as the number of DFCs contained in each state for non-seafarers and seafarers, respectively, where the red line and blue line denote positive FC and negative FC respectively, and the line thickness represents FC strength. Although the figure shows that the number of DFCs contained in each state is different for non-seafarers and seafarers, we cannot directly compare whether there is a significant difference between them due to the difference in fMRI time series and sample number.

Therefore, the ratios of DFC contained in each state for non-seafarers and seafarers and the statistical results between them after T-test with a confidence level of 95% are presented. It can be seen from the figure that there are significant difference between the ratios of non-seafarers and seafarers for state 1, state 3, state 5 and state 6. Among them, each DFC state reflects a FC network between BFNs, and different BFNs show different FCs in different DFC states. For example, all of the DFC states contain both positive and negative FCs except for state 2, and the FCs between most of
the BFNs are positive, while the main BFNs with negative FCs are different in each DFC state.

In particular, the ratios of DFCs contained in states 1, 3, 5, and 6 show significant differences in seafarers compared with non-seafarers, indicating that the brain FC networks corresponding to these four states have significant changed in the brain activities of seafarers. This may be due to the reasons that seafarers have been affected by special occupational factors for a long time, leading to specific transformation in the DFC status between BFNs. For example, CCN and AUN show weak FC in states 1, 3, and 5, while show strong FC in the other four states. The special working and living environment at sea requires AUN and CCN to work together for seafarers, so it has stronger FC than non-seafarers.

**FIGURE 4.** The seven DFC states obtained from the DFCs of all non-seafarers and seafarers at the individual level, and the number of DFCs contained in each state of each group, as well as the ratios of DFCs contained in each state for non-seafarers and seafarers and the statistical results between them. Note: * denotes that there is a significant difference according to T-test with a confidence level of 95%.

**FIGURE 5.** The mean transition probability maps between the DFC states for non-seafarers and seafarers, where (A) represents non-seafarers and (B) represents seafarers. Note that transition probability is color-mapped on a log-scale.

**IV. CONCLUSIONS AND DISCUSSION**

Based on the intrinsic prior information, nine resting-state BFNs in seafarers and non-seafarers were detected by using the GICA-IR method in this study, and statistical analysis was performed on the SFCs and DFCs among the nine BFNs of subjects in the two groups at group level and individual level respectively. It was found that there were no significant difference between the SFCs and DFCs of seafarer and non-seafarer subjects at group-level, as well as SFCs at individual level, but there was a significant difference between the DFCs of them at individual level. Therefore, the sliding time window correlation and clustering analysis methods were used to conduct in-depth analysis on the DFCs of all non-seafarers and seafarers in the following part, and obtained their corresponding seven DFC states respectively. Through the analysis of the differences between the two groups of subjects corresponding to these DFC states, we can found that seafarers' BFNs underwent specific dynamic functional recombination in the process of brain activity, thus presenting some DFC states that were significantly different from those of non-seafarers, and they were likely playing an important role in seafarers' work and life.
When using the sliding window technique for the DFC analysis, the choice of the window length has long been matter of debate. On the one hand, too short window lengths increase the risks of introducing spurious fluctuations in the observed DFC [32, 33] and of having too few samples for a reliable computation of correlation. On the other hand, too long windows will impede the detection of the temporal variations of interest. Based on previous studies that cognitive states could be correctly identified on 30-60s of fMRI data [34], so four different window sizes of 30s, 40s, 50s and 60s width (corresponding to 15TRs, 20TRs, 25TRs and 30TRs), sliding in steps of 1 TR were applied to divide the TC of each IC into 201, 196, 191, 186 windows. Only the results of 40s (20TRs) were presented in the paper, and the relevant results of others three window size were given in Figure 6, which were consistent with the results of 40s (20TRs). These is no obvious difference between the SD of seafarers and on-seafarers at group level, while it has a significant difference between the MSD of seafarers and on-seafarers at individual level according to the results of T-test with a confidence of 95%.

\[ SD \text{ at the group level} \quad MSD \text{ at the individual level} \]

\[\begin{array}{ll}
\text{non-seafarers} & \text{seafarers} \\
\text{non-seafarers} & \text{seafarers} \\
\text{(##)} & \text{(##)} \\
\text{(##)} & \text{(*)} \\
\text{(##)} & \text{(*)} \\
\text{(##)} & \text{(*)} \\
\end{array}\]

**FIGURE 6.** The comparison of standard deviation at group level and mean standard deviation at individual level between non-seafarers and seafarers on the three window widths of 30s, 50s and 60s width (corresponding to 15TRs, 25TRs and 30TRs), as shown in (A), (B) and (C), respectively. Note: # indicates that there is no significant difference through T-test with a confidence level of 95%, and * indicates that there is significant difference.

In order to measure the dynamic difference between the brain functional network connectivity of non-seafarer and seafarer groups, the standard deviation was used to characterize the dynamic variability of each FC in this study, which was obtained by calculating the standard deviation of the corresponding FC on the DFCs of all windows under the condition of each window width. For the DFC analysis at the individual level, the mean standard deviation of the FC at all subjects was used to measure the difference of the dynamic variability between the two groups.

In this paper, the DFC states were extracted from the DFCs of all non-seafarers and seafarers. In order to explore the consistency of DFC states extracted under different conditions, we also considered that extracting the DFC states from the DFCs of non-seafarers and seafarers respectively in the process of DFC analysis, and deeply analyzed the DFC states obtained under these three conditions and the correlation between them, which were presented in Figure 7.

It can be seen from the figure that the DFC states extracted from the DFCs of seafarers and non-seafarers respectively had a good correspondence with the DFC states extracted from all DFCs of seafarers and non-seafarers, but there was no good correspondence between them. In addition, different from previous studies which used k-means clustering to obtain DFC states, the AFC algorithm was adopted to extract DFC states in our study. Because AFC can determine the
number of clusters adaptively, it overcome the problem of pre-determining the number of classification in traditional k-means clustering method and reduces the adverse influence brought by human subjective factors.

![Diagram](image)

**FIGURE 7.** The DFC states obtained using APC from DFCs of non-seafarers and seafarer, as well as the correlation between them with the DFC states obtained from DFCs of all non-seafarers and seafarer, as shown in (A), (B) and (C), respectively.

Furthermore, the nine classical resting-state BFNs involved in this study are closely related to the basic cognitive functions of human. Firstly, DMN is closely related to personal introspection, memory, sensory information processing, thinking reasoning, emotional cognition, social reasoning and interpersonal communication. For seafarers, factors such as changeable sea conditions, monotonous and boring living environment and high-risk working environment, high mental stress and long-term separation from their families can easily cause emotional fluctuations, thinking disorders, psychological anxiety and panic, etc., which have a certain impact on their DMN.

Secondly, VIN and LVN can be divided into both basic and advanced visual networks. Among them, the basic visual network plays an important role in judging the basic features such as the size, shape, color and position of the object, but neurons in the higher cortical area need to participate in the judgment of the influence of external objects and their own and send out instructions to respond at the same time. The advance visual cortex is the region that processes complex cognitive objects and can feedback the processed information to the original visual channel. Since seafarers need to pay attention to the complex situation at sea in real time and give solutions in time, it requires not only the discovery of basic visual cortex, but also the judgment of higher visual cortex and other higher neural activities related to cognition.

In AUN, seafarers often face various kinds of noise when they sail on the sea, such as the sound of the machine and the sound of wind and waves during the voyage continue to occur, which will inevitably have an impact on their AUN. The AUN of seafarer group needs to mobilize more auditory related areas than that of non-seafarer group, so that it can play a significant role in early warning and judgment in emergencies such as severe weather and machine failure during navigation. SMN is mainly used to regulate the motor functions. Seafarers need to adapt to the narrow living space and bumpy living environment when navigating at sea, which will inevitably affect their motor functions to some extent.

ECN and CCN are mainly related to cognitive stimulating activities, such as making plans, making decisions, judging right and wrong, responding to novel environments, and overcoming habitual actions. It needs to coordinate with the visual and auditory networks, and also plays an important role in the regulation of related networks. Since seafarers usually implement semi-militarized management, the ability requirement for executive control is relatively high, which will further strengthen the function of the corresponding brain network. LWMN and RWMN are cognitive systems with a limited capacity that is responsible for temporarily holding information available for processing, which is important for reasoning and the guidance of decision-making and behavior.

However, it was worth noting that some new methods have been used for the functional connectivity analysis in neuroscience, such as high-order FC (HOFC) and functional correlation tensor (FCT). Compared to the traditional temporal synchronization-based low-order FC, HOFC could be used to characterize high-level, more complex FC among the brain regions, which could provide supplementary information to traditional FC [35]. Recently, Zhang et al. proposed an inter-network HOFC method to characterize more complex organizations among the large-scale brain networks, and demonstrated its biological meaning and potential diagnostic value in clinical neuroscience studies as a useful complement to the traditional inter-network FC methods [36]. While FCT could be used to obtain the white matter (WM) information which was usually measured by diffusion tensor imaging [37]. For example, Chen et al. adopted FCT to obtain the valuable functional information in the WM, and then combining it with the dynamic FC in the gray matter for the classification of mild cognitive
impairment subjects, which significantly improved the diagnosis accuracy even using resting-state fMRI data alone [38]. Therefore, we will also consider applying them to analyze the occupational brain plasticity of seafarers in our future studies.

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