

# Dynamic Functional Connectivity Analysis of Seafarer's Brain Functional Networks

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**Abstract**—As a special occupation, Seafarers often face different working and living conditions compared to the terrestrial environment, so it is very important to explore the influence of maritime environment on seafarers' brain function. Based on the eight typical resting-state brain functional networks obtained by group independent component analysis, this paper adopt sliding temporal window and affine propagation clustering methods to deeply analyze the differences of dynamic functional connectivity between seafarers before and after sailing with those between seafarers and non-seafarers corresponding to these networks. The results show that the dynamic change among the eight brain functional networks between seafarers before and after sailing has obvious differences with those between non-seafarers and seafarers, which mean that the impact of marine environment on the seafarers' brain functional networks has certain timeliness. Some changes of the brain functional connectivity networks can be recovered within a certain period of time, while others may have long-term effects on the connections between brain functional networks, so as to reorganize the topological relationship between brain functional networks and form the unique brain network biomarkers of seafarers, which has a great significance to explore the plasticity of seafarer's brain functional networks and the neural rules of sea-farer's brain functional activities.

**Index Terms**—fMRI, dynamic functional connectivity, affine propagation clustering, brain network, seafarer

## I. INTRODUCTION

As a newly emerging neuroimaging technology, functional magnetic resonance imaging (fMRI) has many unique advantages compared with other imaging technologies, and it has been fulfilled in various fields of brain research. The functional connectivity (FC) analysis based on resting-state fMRI as a mainstream neuroimaging method has been widely applied in the diagnosis and prediction of neurological diseases [1] and the cognitive neural mechanism of special occupations [2]. A common assumption used in these studies is the temporal stationary of FC, where the FC is measured over the entire time period. Therefore, the brain network information is assuming that the network model has the invariance of the human brain, and in constructing the

network model is to take the entire period of the human brain time series data to construct a static network [3].

Although the temporal stationary of FC provides a simple and convenient frame-work for us to examine large-scale brain networks and explore the correlation between functional and structural connectivity [4], [5]. However, the time series in fMRI data is usually not stability, so it is difficult to guarantee the premise of temporal invariant, and researchers have found that only considering static FC is not enough to explain the time-varying and dynamic information interaction of brain network between different regions [6], [7]. Instead, the dynamic nature of FC should be studied to reveal the complex and changeable characteristics and mechanism of the brain network [8], [9]. Therefore, the research should consider the time-varying characteristics and construct a dynamic brain network when constructing the human brain network model, so as to better mine the information of the human brain network [10], [11].

In recent years, many studies have shown that the dynamic FC (DFC) analysis can provide a better study on the neurocognitive mechanism of special occupational groups, but there are also some problems and limitations. For example, Shen et al. investigated how the dynamics of resting-state FC are linked to driving behavior using a sliding window approach [12]. Shi et al. investigated dynamic functional connectivity among large-scale brain networks during resting state fMRI in relation to subjective well-being (SWB) in two large independent datasets [13].

As a special professional group, seafarers have different working conditions on the sea compared with those in terrestrial environment, which make the seafarers easy affected by the natural and working environments as well as many other complex factors, and leads to changes in the FC of seafarer's brain [14], [15]. Therefore, it is very important to explore the influence of maritime environment on seafarers' brain. Recently, Wang et al. used a dynamic functional connectome characterization (DBFCC) 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 in seafarers. The results reflected the functional plasticity only existed in the seafarers, which showed close relationships with the long-term career experience of sailors [16]. But there are

no studies that have taken into account the dynamic variation characteristics of fMRI brain functional networks, especially for the differences in the long-term and short-term effects of marine environment on seafarers' brain functional activities.

In this study, the fMRI technology is applied to explore the impact of maritime environment on the brain functional networks of seafarer before and after sailing, as well as the differences compared with those of non-seafarer. Particular, group independent component analysis (GICA) was used to obtain the brain functional networks of seafarer and non-seafarer groups, and then the sliding temporal window correlation was adopted for the DFC analysis between these brain functional networks. Next, the affine propagation clustering (APC) algorithm was used to extract the intrinsic dynamic functional states existed in the DFCs of seafarer and non-seafarer groups. Through compared the results of seafarer before and after sailing with those of non-seafarer, the research identified the long-term and short-term effects caused by the special working and living conditions at sea on seafarers as well as their differences, which had a great significance to accurately explain and reflect the functional plasticity of seafarer's brain.

## II. MATERIALS AND METHODS

### A. Data Description

The resting-state fMRI data of 33 seafarers before and after sailing were involved in this study, and all of them came from a shipping company of Shanghai. So there are a total of 66 fMRI dataset, which were divided into two groups. The data of seafarers before sailing was denotes presailor group, and the data of seafarers after sailing was denoted as backsailor group. 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. The fMRI data were acquired in the Shanghai Key Laboratory of Magnetic Resonance of the East China Normal University on a 3.0T 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  $64 \times 64$ . The in-plane resolution was  $3.75 \times 3.75 \text{ mm}^2$ , and the slice thickness was 4 mm.

The resting-state dataset was downloaded from the public neuroimaging database (<http://www.nitrc.org/projects/fcon1000/>), which was denoted as the healthy control group of non-seafarers. This dataset was released by Dr. James J. Pekar and Dr. Stewart H. Mostofsky, and included 23 healthy subjects in total. The fMRI data were acquired on a 3.0T scanner using a gradient echo EPI with 47 slices providing whole-brain coverage and 123 volumes, a TR of 2.5 s and a scan resolution of  $96 \times 96$ . The in-plane resolution was  $2.67 \text{ mm} \times 2.67 \text{ mm}$ , and the slice thickness was 3 mm.

### B. Data Preprocessing

In the experiments, the fMRI data processing was performed using DPARSF software

(<http://rfmri.org/DPARSF>) and custom code written in Matlab 2016a. The rigid body motion correction was performed to correct for subject head motion followed by slice-timing correction to account for timing differences in slice acquisition. Then the fMRI data were subsequently warped to a Montreal Neurological Institute (MNI) template and resampled to  $2 \text{ mm}^3$  isotropic voxels. Finally, the data was smoothed by Gaussian smoothing with a 4 mm full width at half maximum (FWHM). In addition, the time course of each voxel was variance normalized prior to perform GICA as this has shown to better decompose subcortical sources in addition to cortical networks. Furthermore, the location and display of these networks were assessed by using the MRIcro software (<http://www.mricro.com>).

### C. Dynamic Functional Connectivity Analysis

In the field of fMRI data analysis, the simplest strategy for investigating DFC is to divide the time series into a set of time windows from different spatial locations (brain regions or regions), and then studying their pairwise connectivity in each time window. Subsequently, fluctuations in connectivity can be captured by collecting descriptive measurements of FC on a series of time windows, which is why the term dynamic FC was coined. Many methodological choices and extensions to this straightforward framework have been suggested, including in particular: (1) the choice of the most suitable window characteristics (length and shape) and alternative approaches to overcome window limitations; (2) different measures to assess FC inside the window; (3) how to extract interpretable information from the DFC patterns, either by assessing graph measures or by determining DFC states. Among them, sliding temporal window correlation analysis is the most classical DFC analysis method, which will be used in this study.

### D. Group Independent Component Analysis

After preprocessing the fMRI data, functional data from both seafarer and non-seafarers groups were analyzed using spatial GICA framework, which was implemented by using the GIFT software (v2.0e) (<http://mialab.mrn.org/software/>) [17], [18]. Spatial ICA decomposed the fMRI data into linear mixtures of spatially independent components (ICs) with a unique time course profile, which included two dimensionality reduction steps. For the subject-specific data reduction step, principal component analysis (PCA) was used to reduce 120 time point data into 39, 160 time point data into 62 and 160 time point data into 63 maximum variability directions for non-seafarer, presailor and backsailor groups, respectively. Then the subject-specific reduced data were concatenated across temporal dimension and a group data PCA step reduced this data further into 26, 41 and 42 components for non-seafarer, presailor and backsailor groups along maximum group variability directions. The ICs were obtained from the group PCA reduced fMRI data using FastICA algorithm [19]. In particular, ICA algorithm was repeated 20 times in ICASSO to obtain reliable ICs [20], and minimum description length (MDL) was used to estimate the

number of ICs [21]. The aggregate spatial maps were estimated as the modes of component clusters. Subject specific spatial maps (SMs) and time courses (TCs) were obtained using GICA back reconstruction approach implemented in GIFT software.

### E. Sliding Temporal Window Analysis

When obtained the ICs of each subject in the groups of non-seafarer, presailor and backsailor through GICA, eight typical resting-state brain functional networks (BFNs) of interest were selected using prior information for the following analysis, including visual network (VIN), default mode network (DMN), lateral visual networks (LVN), cognitive control network (CCN), working memory network (WMN), salience network (SAN), auditory network (AUN) and sensorimotor network (SMN), and these brain networks have also been reported in some previous literatures [22-24].

Next, the sliding temporal window correlation method was used to implement the DFC analysis between these BFNs for each group. The time courses corresponding to these eight BFNs were used to construct the DFC matrices according to the window width of 20TRs with a step-length of 1TR. The DFC matrix represents the Pearson correlation coefficient between each pairs of the corresponding time series of eight BFNs. Therefore, there were a total of 101,141 and 141 DFC matrices for the groups of non-seafarer, presailor and backsailor, respectively.

Finally, the APC algorithm was used to extract the intrinsic DFC states from the DFC vectors corresponding to DFC matrices of all subjects in seafarer and non-seafarer groups, where the DFC vector was obtained according to upper triangular elements of DFC matrix by row expansion, so that there were 11629 DFCs matrices in total. Six implicit DFC states were obtained, and a detailed statistical analysis of the DFC states between the groups of non-seafarer, presailor and backsailor was conducted.

## III. RESULTS AND ANALYSIS

In this section, the results of DFC analysis between eight typical resting-state BFNs are presented, which obtained using GICA with APC on the non-seafarer and seafarer fMRI datasets, respectively.

Figure 1 shows the eight resting-state BFNs and their corresponding MNI coordinates obtained by analyzing the brain functional connectivity of seafarers and non-seafarers at the group-level using GICA. These BFNs included VIN, DMN, LVN, CCN, WMN, SAN, AUN and SMN, which are obtained with threshold  $|z| \geq 2$  after z-scored the ICs of GICA, as shown in (A)-(C) for non-seafarer, presailor and backsailor groups, respectively.

Figure 2 shows the six DFC states of the eight BFNs existed in the whole time series, which obtained using APC from the DFC vectors of all subjects in the groups of non-seafarer, presailor and backsailor. It can be seen from the figure that state 3 and state 4 are similar to each other in BFNs except for their different FC strengths, but they differ significantly from state 1, state 2, state 5 and

state 6. Thus, it is confirmed that the eight BFNs in this study are indeed in dynamic change during the whole time series, presenting different FC states.

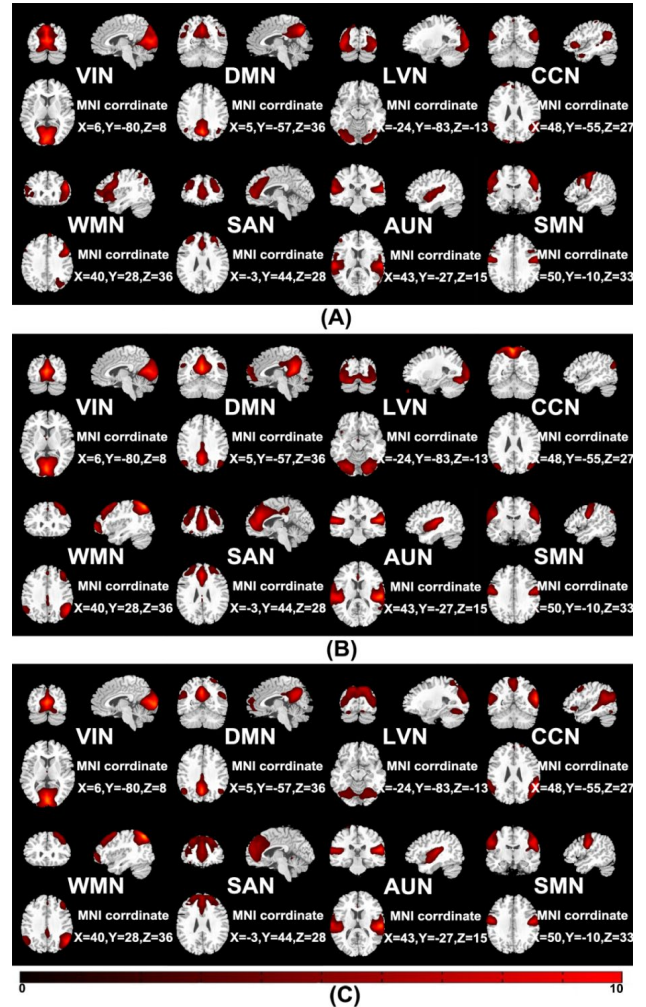


Figure 1. The eight resting-state BFNs of VIN, DMN, LVN, CCN, WMN, SAN, AUN and SMN, which are shown in (A)-(C) for the groups of non-seafarer, presailor and backsailor, respectively. The spatial maps of these BFNs are obtained with threshold  $|z| \geq 2$  after z-scored the ICs of spatial ICA.

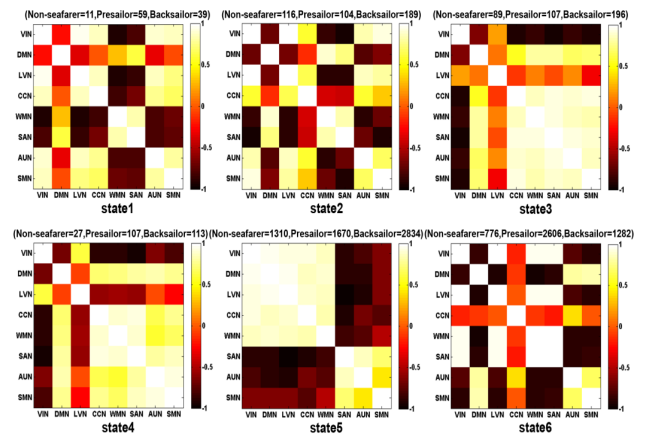


Figure 2. The six DFC states of the eight BFNs obtained from the DFC vectors of all subjects in non-seafarer, presailor and backsailor groups, as well as the number of DFC vectors contained in each state for each group.

Meanwhile, the number of DFC vectors obtained in each DFC state for the three group subjects is also presented, respectively. Although the number of DFC vectors contained in each state is different between non-seafarer and seafarer groups, it cannot be judged that there is a difference between them in this state. This is due to the reason that the length of time series in fMRI data corresponding to seafarers and non-seafarers is inconsistent, so the number of DFC vectors is not the same in different groups under the condition of the same window width. In particular, when the window width of 20TRs with a step size of 1TR was used in this study, the number of DFC vectors corresponding to the groups of non-seafarer and seafarer were 2323 and 4653, respectively. Therefore, it is impossible to judge whether there are differences between them directly from the number of DFC vectors contained in the state, which requires further detailed analysis, as shown in Figure 3.

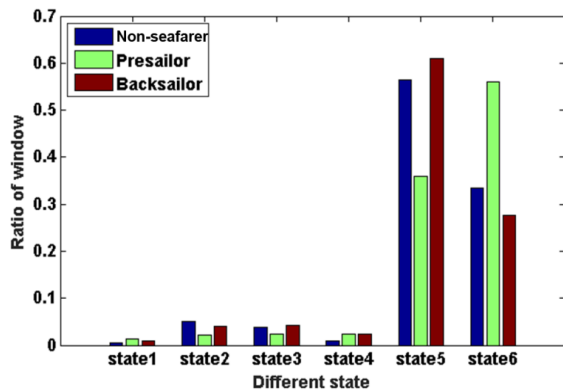


Figure 3. The comparison of the ratio of DFC vectors included in each DFC state among the three groups of non-seafarer, presailor and backsailor.

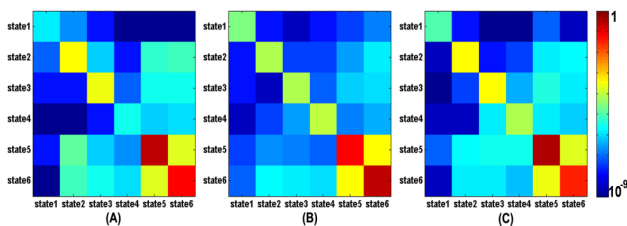


Figure 4. The average state transition probability diagram for the groups of non-seafarer, presailor and backsailor, which are shown in (A)-(C), respectively. Note that transition probability is color-mapped on a log-scale.

Figure 4 presents the average state transition probability diagram of the six DFC states existed in the eight BFNs for the non-seafarer, presailor and backsailor groups, as shown in (A)-(C). It can be seen from the figure that all of the states remain in their own state except for state 1. Among them, each group of subjects had a long existence on state 5 and state 6, which is consistent with the fact that they remain in their own state for a long time. While the transition probability is low between different states, and the big one is the transition between state 5 and state 6. It further indicates that this two DFC states are the main survival state of these eight DFNs in the whole time process, which needs to be paid more attention.

#### IV. CONCLUSIONS AND DISCUSSION

In this study, the GICA and sliding temporal window correlation analysis with APC was used to explore dynamic variation differences among eight resting-state BFNs in non-seafarer and seafarer groups. The results showed that the dynamic changes of seafarers' eight BFNs between before and after sailing are obviously different from those between non-seafarers and seafarers, which mean that the influence of maritime environment on seafarers' brain functional networks can be divided into short-term and long-term. Short-term effects can be recovered within a certain period of time, while long-term effects can reorganize the connections between BFNs and may be form unique plasticity biomarkers corresponding to the occupational group of seafarers.

In this paper, the sliding temporal window method is used to divide the time series in fMRI data and construct the DFC matrix, in which the window width is a very important factor. Based on the previous studies that have shown that cognitive states could be correctly identified on 30-60s [25], the window width of 40s corresponding to 20TRs with sliding in a step of 1 TR was used in our study, which was applied to divide the time series of each brain network into 101, 141 and 141 windows for non-seafarer, presailor and backsailor groups, respectively. In addition, the APC was used to extract the DFC states from the DFC vectors which concatenated DFC matrices across all subjects. Compared with the k-means algorithm used in the traditional method, it does not need to determine the number of clusters. Feature weighting and sample weighting are considered in this clustering algorithm and the cluster number is automatically set by using the cluster validity index to finish clustering.

According to the comparison of the DFC results among the eight resting-states BFNs between seafarers before and after sailing with those between seafarers and non-seafarers, it can be found that the effects of the marine environment on the seafarer's BFNs are time-sensitive. Some changes can be recovery in a certain time, while others may be have long-term effects on the BFNs, thus forming some unique professional brain plasticity biomarkers. In the following research, we will obtain more data to analyze the changes of dynamic brain functional connectivity networks between seafarers before and after sailing with those between non-seafarers and seafarers in a more in-depth way.

#### AUTHOR CONTRIBUTIONS

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#### CONFLICT OF INTEREST

The author declares no conflict of interest.

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