Mid-Task Physical Exercise Keeps Your Mind Vigilant: Evidences From Behavioral Performance and EEG Functional Connectivity

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***Abstract*— Accumulating efforts have been made to discover effective solutions for fatigue recovery with the ultimate aim of reducing adverse consequences of mental fatigue in real life. The previously-reported behavioral benefits of physical exercise on mental fatigue recovery prompted us to investigate the restorative effect and reveal the underlying neural mechanisms. Specifically, we introduced an empirical method to investigate the beneficial effect of physical exercise on the reorganization of EEG functional connectivity (FC) in a two-session experiment where one session including a successive 30-min psychomotor vigilance task (PVT) (*No-intervention session*) compared to an insertion of a mid-task 15-min cycling exercise (*Intervention session*). EEG FC was obtained from 21 participants and quantitatively assessed via graph theoretical analysis and a classification framework. The findings demonstrated the effectiveness of exercise intervention on behavioral performance as shown in improved reaction time and response accuracy. Although we found significantly altered network alterations towards the end of experiment in both sessions, no significant differences between the two sessions and no interaction between session and time were found in EEG network topology. Further interrogation of functional connectivity through classification analysis showed decreased FC in distributed brain areas, which may lead to the significant reduction of network efficiency in both sessions. Moreover, we showed distinct patterns of FC alterations between the two sessions, indicating different information processing strategies adopted in the *intervention session*. In sum, these results provide some of the first quantitative insights into the complex neural mechanism of exercise intervention for fatigue recovery and lead a new direction for further application research in real-world situations.**

***Index Terms*— Fatigue recovery, functional connectivity, physical exercise, EEG, classification.**

Manuscript received July 6, 2020; revised September 4, 2020; accepted October 1, 2020. Date of publication October 14, 2020; date of current version February 25, 2021. This work was supported in part by the National Natural Science Foundation of China under Grant 81801785, in part by the Hundred Talents Program of Zhejiang University, in part by the Fundamental Research Funds for the Central Universities under Grant 2019FZJD005 and Grant 2020FZZX001-05, in part by the Zhejiang Laboratory under Grant 2019KE0AD01, and in part by the Navy Aviation Equipment Research Project under Grant HJ20172A02133. *(Corresponding authors: Chuantao Li; Yu Sun.)*

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Digital Object Identifier 10.1109/TNSRE.2020.3030106

I. Introduction

EXCESSIVE demands of prolonged daily activities on cognitive systems are associated with mental fatigue, usually manifested as the performance deterioration caused by failure to maintain vigilant attention [1], [2]. Specifically, longer response time and more operation lapses/errors [3] may lead to a decrease in work efficiency or even have serious consequences. For example, driving or medical accidents have been consistently revealed to be attributed at least partly to sleepiness and/or fatigue [4], [5]. To reverse these detrimental effects, continuous efforts have been made to investigate the underlying neural mechanism of mental fatigue [6]–[8]. Moreover, effective means of fatigue recovery are correspondingly needed to help regain vitality and cope with immediate work, which is extremely important for maintaining daily production as well as improving operation safety.

Among the limited researches on fatigue recovery, rest is the most common countermeasure to be utilized. For instance, Lim and Kwok [9] investigated the effect of rest intervals of 1, 5, or 10 min on mental fatigue during the execution of a 1-hr auditory task, and showed that longer rest break brought greater improvement in reaction time (RT), but a significantly steeper decline in performance was observed in the subsequent task. Similar results were found by the same group in their recent study of a self-paced blocked symbol decoding task (BSDT) with 12 s or 28 s breaks [10], the implicit resource deployment in post-break period was changed by the length of mid-task rest. However, in our previous study [11], no significant difference in task performance was detected between the mid-task break session and the no-break session. Inconsistent findings among these studies may be due to different characteristics of rest breaks, such as the length of rest and the nature of break. Of note, Helton and Russell [12] reported that specific activities during the break are important moderators of recovery. The study investigated the visuospatial vigilance performance after different interruptions, and revealed the best performance post-interruption was for rest break, worst for continuous vigilance task, and varied for other interruption tasks. They explained that there may be interference when the primary task and activities occupy the same resources. To further explore different ways of fatigue recovery in addition to performing tasks, Li and Sullivan [13] reported green landscapes could promote students to recover from stress and mental fatigue during the breaks. However, finding the right environment to reduce mental fatigue may not be straightforward [14]. In addition, numerous studies have shown continuous aerobic exercises of moderate intensity are beneficial to attention in people of different ages [15]. For instance, cancer patients in the exercise program were reported to show less increase in fatigue [16]. Similarly, Ashrafinia *et al.* [17] explored the effect of Pilates exercises on postpartum fatigue, and the results showed physical exercise reduced the level of mental fatigue. Nevertheless, the training foundation is required for these regular exercises, and the mental fatigue and recovery mechanisms of patients are likely to be different from normal people [18]. Thus, the neural mechanism of acute exercise on mental fatigue recovery in healthy individuals has been almost ignored.

The measurements of behavioral data and brain activity indicators are widely used in fatigue-related studies to quantify the effects of mental fatigue recovery. Regarding the evaluation of brain activity, electroencephalogram (EEG) is increasingly utilized for its high temporal resolution, comfort to wear, and more importantly applicability of transferring to real-life conditions [7]. Tops and Boksem [19] reported the shift of EEG power toward low-frequency bands with increasing fatigue may be related to the decrease of arousal level. Moreover, numerous fatigue studies have found that frontal theta EEG activity is closely related to cognitive control by investigating response monitoring [19], [20]. Moreover, recent advances in brain networks and graph theoretical analysis have gained substantial interest in fatigue studies for its strength in providing the scene of synchronization changes among different brain regions. For instance, network functional connectivity (FC) was employed in the state classification of mental fatigue induced by psychomotor vigilance task (PVT) [21]. Using the same experiment of PVT, cortical FC analyses were implemented to investigate the neural mechanism of mental fatigue [22]. The findings demonstrated the effectiveness of PVT in inducing mental fatigue, and the most discriminative connectivity features were discovered in the middle frontal gyrus and motor areas. In a simulation study of daily activities, the investigation of driving fatigue revealed the altered network topology and information integration capabilities [23]. They found increased coherence in the frontal, central and temporal regions, and clustering coefficient for alpha, beta, and delta bands and the characteristic path length for all bands were also increased. Thus, the low wiring costs in the functional networks and disruption in the effective connections between and across cortical areas were demonstrated, and a more economic but less efficient configuration of topology structure in driving fatigue was reported. The different fatigue paradigms posed a question whether the level of mental fatigue caused by simulated driving [8], [24], [25] is similar to that caused by cognitive tasks [11], [22]. Most recently, Dimitrakopoulos *et al.* [26] conducted a study to reveal and systematically compare different neural mechanisms of fatigue underlying simulate driving and cognitive task. The study showed distinct network reorganizations between these two paradigms, which indicates the complex neural mechanisms of mental fatigue and points out the role of workload on mental fatigue. As described above, brain network analyses were widely employed to explore the complex mechanism of mental fatigue, and the changes of brain signals related to mental fatigue were effectively measured. However, there is a lack of research on the brain network reorganization of EEG signals during fatigue recovery.

Fatigue recovery is related to the nature of the intervention [7]. To the best of our knowledge, no literature has explored the neural mechanism of exercise intervention on fatigue recovery in healthy adults. Therefore, we adopted the network evaluation method of FC to investigate the effect of mid-task physical exercise on mental fatigue. A continuous 30-min PVT experiment was implemented in the *no-intervention session*, while the *intervention session* included a 15-min cycling in the middle of the task. According to the resource theory, repeated consumption of finite cognitive resources that cannot be replenished immediately would lead to vigilance decrements and performance deterioration [27]. Moreover, the benefits of aerobic exercise on executive function [28] and mood states [29] have been already demonstrated. We made a hypothesis that mid-task physical exercise would lead to recovery of mental resources, which could be shown in the behavioral data and network analyses. In the present study, we directly focused on the activities of alpha and theta bands, which are reported to be reliable measurements of mental fatigue [20]. EEG FC was constructed by the phase lag index (PLI) based on these two bands to evaluate the phase synchronization of all pairs of channels. Subsequently, we calculated network metrics to quantitatively assess alterations of functional brain networks. A further investigation was performed for state classification, which would provide localized changes in FC caused by exercise intervention on task execution.

II. Materials and Methods

A. Participants

Twenty-four participants recruited from Zhejiang University were right-handed students (13 males, age: 22.0 $\pm$ 2.8 years), and they reported normal or corrected-to-normal vision. These participants were pre-screened to exclude those with chronic

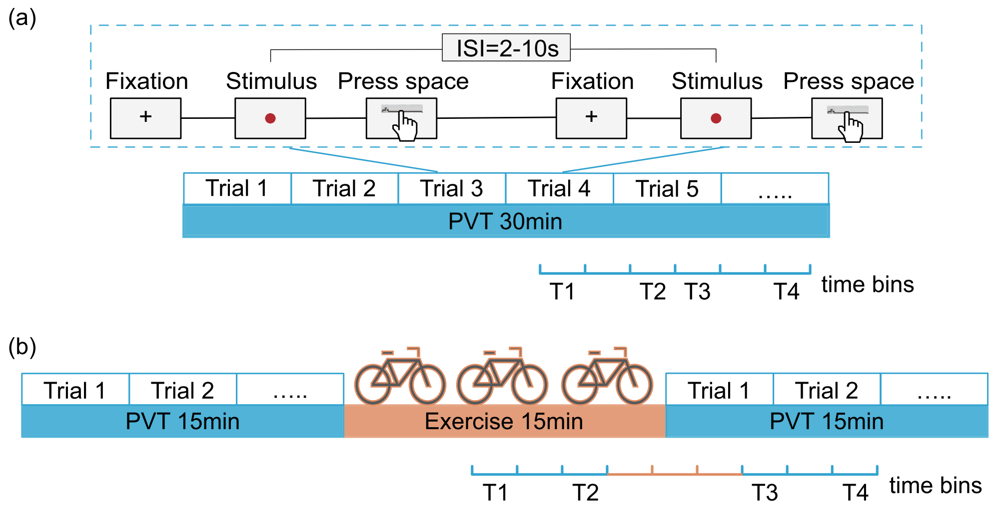

Fig. 1. The experimental paradigm. (a) Participants performed a 30-min PVT in the *no-intervention session*. Each participant was asked to press the space bar as soon as possible when the red stimulus appeared. The inter-stimulus interval (ISI) is a random value in the range of 2 - 10s. The 30-min PVT was divided into six 5-min time bins, T1 and T4 correspond to the first and last time bins, respectively. T2 and T3 correspond to the two time bins in the middle. (b) In the *intervention session*, participants were required to perform a 15-min cycling in the middle of the PVT execution. The PVT before and after the exercise intervention was divided into 5-min time bins, T2 and T3 correspond to the pre- and post-intervention time bins, respectively.

physical or mental illness such as high blood pressure, diabetes, sleep disorder, or long-term medication. Meanwhile, they were required to get a minimum of 7 h of sleep for 2 days prior to the study, and not to drink alcohol or coffee and to perform strenuous activities before the experiment. Written informed consent was obtained from each participant after the explanation of the whole experiment. The study was conducted in compliance with relevant laws and institutional guidelines and approved by the Institutional Review Board of Zhejiang University (IRB2019001).

B. Experimental Settings

To explore the recovery effect of mid-task physical exercise, a within-subject experiment was designed in this study. Participants performed a 30-min PVT in the *no-intervention session*, while in the *intervention session*, 15-min mid-task cycling was conducted after a 15-min PVT and followed by another 15-min PVT. There was a one-week interval between the execution of the two sessions, and the session order was counterbalanced. On arrival of the laboratory, participants were introduced to the entire experiment process when preparing for EEG recording. To avoid the training effect, subjects first practiced until they were familiar with the PVT procedure. A schematic diagram of the experimental setup is shown in Fig. 1. Briefly, once the stimulus was presented, participants were required to press the space bar as quickly as possible. The inter-stimulus interval (ISI) was a random value between 2 and 10 s (mean $= 6$ s). A detailed introduction to PVT has been described previously [22]. False responses less than 100 ms and lapses greater than 500 ms were rejected in subsequent analysis. The PVT duration is typically 10 min, here, a 30-min PVT was employed to elicit greater levels of fatigue. Moreover, participants used a Monark 975 stationary exercise bicycle to perform moderate-intensity exercise in the *intervention session*. They were required to maintain aerobic exercise with 55% - 65% intensity of heart rate reserve (HRR) during the exercise execution. The subjective fatigue states of each participant were evaluated by short stress state questionnaire (SSSQ) [30] prior to and after each session. Task engagement, distress, and worry factors were measured in the 24-item SSSQ.

C. EEG Recordings and Pre-Processing

EEG data were recorded as participants conducted the 30-min PVT through a 64-channel BrainAmp EEG amplifier (Model: Brain Products, Gilching, Germany) according to the international 10 - 20 system. The impedance of each electrode was controlled below 5 kΩ during data collection, and a 50 Hz notch filter was employed to avoid main interference. Standard pre-processing procedures were adopted. Raw EEG signals were digitized at a sample rate of 256 Hz, bandpass filtered (0.1 – 45 Hz), and average re-referenced. Moreover, the artifacts of blinking and muscle activities were removed by independent components analysis (ICA). EEG signals in each trial were then segmented into epochs in the range of 0 – 500 ms after the stimulus onset, the epochs in 5 min were collected to explore the changes of fatigue states, thus the 30-min PVT was divided into six 5-min bins in both sessions. Data of three subjects were excluded due to the recording failure or incomplete information. The remaining 21 participants were further analyzed. All preprocessing procedures of EEG signals were carried out using in-house scripts and EEGLAB toolbox [31].

D. Network Connectivity

To obtain reliable estimates of phase synchronization that are invariant against volume conduction, PLI method was utilized to construct the FC [32]. The validity of PLI in detecting intrinsic characteristics of physiological signals has already been proven [33]. Let $x_j(t)$ represents a real-time series of the jth channel, the instantaneous phase $\phi_j(t)$ of the channel was calculated as:

$$\phi_j(t) = arctan(\frac{\widetilde{x}_j(t)}{x_j(t)}), \tag{1}$$

where $\widetilde{x}_j(t)$ is the Hilbert transform for $x_j(t)$. If $\phi_k(t)$ indicates a real-time series of the kth channel, the difference in phase between two channels can be expressed as:

$$\Delta\phi(t) = \phi_j(t) - \phi_k(t). \tag{2}$$

PLI is an index of the asymmetry of the phase difference distribution, which can be obtained from a series of phase differences $\Delta\phi_{j,k}(t_i)$, $i = 1, \ldots, N$ in the following way:

$$PLI_{j,k}(t) = |< sign[\Delta\phi_{j,k}(t_i)] >|, \tag{3}$$

where $< \bullet >$ refers to the mean value, $|\bullet|$ is the absolute value, and sign denotes signum function. PLI values range between 0 and 1, e.g., a value of 0 means either no coupling or coupling with a phase difference centered around 0 and π, while a value of 1 shows perfect phase locking with a completely consistent phase difference. The above PLI calculation was performed for all pairs of channels and assembled to form a connectivity matrix. Meanwhile, EEG time series for each session were decomposed into theta ($4 - 7$ Hz) and alpha ($8 - 12$ Hz) frequency bands. PLI was calculated in each trial and then averaged within the 5-min bin, and finally, a 63×63 weighted adjacency matrix was obtained in each band. The estimation of PLI was realized through in-house scripts written in MATLAB R2018b (The MathWorks Inc., U.S.).

E. Network Analysis

The characteristics of functional brain networks could be measured by corresponding network metrics. Prior to the network analysis, the sparsity threshold was adopted to remove a large number of uncorrelated or weakly correlated spurious connections and maintain a consistent wiring cost. Specifically, a sparsity means the ratio of actual edges to the number of possible edges in the network [34]. Given that no clear definition of an accurate threshold has been made, a wide sparsity ranging from 0.1 to 0.3 with a step of 0.01 was employed in this work to preserve the reachability of the functional network and small-world properties. To provide explicit physical meaning to the concept of small-world properties, the efficiency of information transfer was employed to measure the changes of network properties in the *intervention* and *no-intervention sessions*. Specifically, the global efficiency (E_{glob}) and local efficiency(E_{loc}) of the brain network were estimated [35], [36]. E_{glob} measures the global efficiency of parallel information transfer throughout the network. For a weighted network, the global efficiency is obtained as:

$$E_{glob} = \frac{1}{N(N-1)} \sum_{i \neq j \in G} \frac{1}{L_{i,j}}, \tag{4}$$

where the shortest path length L between node i and j is the smallest sum of the physical distances throughout all the possible paths in the graph. E_{loc} indicates how well each subgraph exchanges information when the index node is eliminated, which is defined as:

$$E_{loc} = \frac{1}{N} \sum_{i \in G} E_{glob}(i) = \frac{1}{N}(\frac{1}{N_{G_i}(N_{G_i}-1)} \sum_{j,k \in G_i} \frac{1}{L_{j,k}}), \tag{5}$$

where N_{G_i} is the number of nodes in the subgraph (G_i) of the neighbors of node i. To further balance individual differences and avoid significant differences caused by the arbitrary selection of a specific threshold, the integrated network metrics were adopted over the predetermined range of sparsity. Specifically, the integrated values correspond to the areas under the metric curve [36]. The implementation of graph theoretical metrics estimation was based on the Brain Connectivity Toolbox [34].

F. State Classification and Discriminative Feature Identification

The alterations of FC in different states were investigated by performing state classifications using the PLI as features. To remove the substantial irrelevant connectivity and avoid the possible overfitting issue due to the fact that the number of features is much larger than that of samples, linear support vector machine recursive feature elimination (SVM-RFE) with correlation bias reduction (CBR) [37] was utilized. SVM-RFE is a backward elimination method, which starts with a full feature set, then selecting important and independent features in succession based on the coefficients calculated from the SVM model. Given that correlations of FC in brain network may cause the importance of features to be underestimated, the CBR method was employed to reduce this correlation bias. The stability and effectiveness of the SVM-RFE+CBR ensemble method have already been verified [38]. When the method converges, a ranked feature space of all features is constructed based on the discriminative power.

It is worth noting that studies have shown recovery effects of rest intervention were transient [10], with longer rest leading to faster performance deterioration after the post-break improvement in behavior. Thus, we chose four time bins (T1, T2, T3, and T4) to explore the immediate effect and the general effect of mid-task exercise. In particular, the immediate effect was evaluated by comparing the pre-intervention time bin with the post-intervention time bin (i.e., T2 *vs*. T3). Since the first (T1) and last (T4) bins of the task represent the most alert and fatigued states in both sessions, the general recovery effect of exercise intervention was assessed via comparing these two time bins between both sessions (Fig. 1). Therefore, two groups of classifications were performed in the *intervention* and *no-intervention sessions* respectively to analyze the immediate (i.e., T2 *vs*. T3) and general (i.e., T1 *vs*. T4) effects of mid-task exercise on brain networks. For each participant, feature vectors cross epochs for alpha and theta bands were merged to obtain the original dataset ($2 \times 63 \times (63 - 1) / 2 = 3{,}906$ features). Subsequently, the SVM-RFE+CBR method was applied in all the data, and two ranked feature sets of each session were obtained based on the significance of each feature. For the selection of optimal features, the classification accuracy was calculated by successively adding one-by-one the previously ranked features with a null feature set. Through the evaluation of different numbers of features, the optimal feature subset with the highest classification accuracy was obtained. Taking into account the small number of samples and the possible effect of training set variability, the optimal feature selection and the classification were performed 100 repetitions, and 10-fold cross-validation was used. Training and testing were done by randomly splitting all data for the cross-validation folds.

G. Statistical Analysis

To analyze the difference in self-report states before and after the task, three factors of SSSQ (engagement, distress, and worry) were first analyzed using repeated-measures ANOVA. Then paired t-test was used to measure the changes of behavioral RT with the execution of both sessions. Furthermore, repeated-measures two-way ANOVA with factor #1 session (i.e., intervention $vs.$ no-intervention), factor #2 time (i.e., T1 $vs.$ T4) was implemented to explore the general effect of exercise intervention on RT, accuracy, and integrated network metrics. Similarly, the immediate effect brought about by mid-task exercise was evaluated by comparing time bins before and after the exercise intervention (i.e., T2 $vs.$ T3). The Bonferroni method was employed for the post-hoc test. The probability value less than 0.05 ($p < 0.05$) was considered significant. Statistical analyses were performed by the SPSS 25 software (IBM, New York).

To estimate the significance of the classification accuracy, the permutation test suitable for small samples was performed [39]. The test was conducted 1000 times through the random permutation of class labels to achieve reliable results. The statistic P-value was calculated as the proportion in the randomized samples greater or equal to that in the original samples. Classification accuracy is significant when the p value is less than 0.05.

III. Results

A. Behavioral Results

Statistical analyses for three factors of SSSQ were carried out. The engagement and distress factors of the SSSQ questionnaire showed significant time effects, while no significant difference was shown in the worry factor. The post-session engagement decreased significantly ($F_{1,20} = 19.151$, $p < 0.001$) in both conditions. However, the interaction effect was not statistically significant. Meanwhile, participants were significantly more distressed ($F_{1,20} = 12.755$, $p = 0.002$) after performing the experiment.

The RT and accuracy in each 5-min bin were averaged to show the behavioral performance of the participants (Fig. 2). To evaluate the state before exercise intervention, paired t-test was performed and found consistent fatigue states between the two sessions. The RT in the second time bin (T2) increased significantly compared to the first 5-min bin (T1) in the *intervention* ($t_{20} = -4.933$, $p < 0.001$) and *no-intervention* ($t_{20} = -7.208$, $p < 0.001$) *sessions*. With the introduction of mid-task exercise, the performance of the

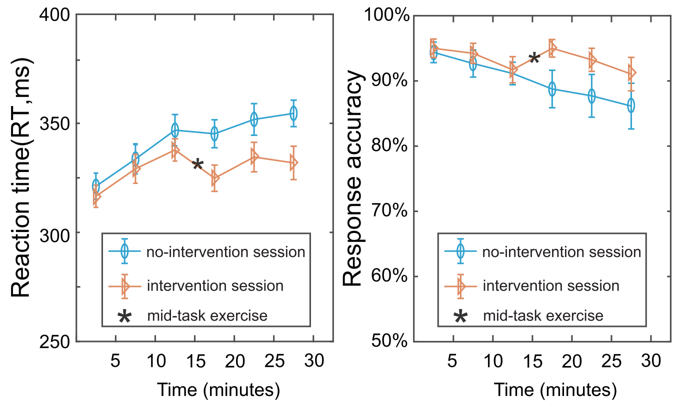

Fig. 2. Behavioral results. Mean and standard error of RT and accuracy were calculated within each 5-min bin in both sessions.

TABLE I
Statistical Comparisons of Behavioral Results

Effect	Two-way repeated measures ANOVA		
	Session effect $F_{1,20}(p)$	Time effect $F_{1,20}(p)$	Interaction $F_{1,20}(p)$
General effect (T1 $vs.$ T4)			
Reaction time	**9.633 (0.006)**	**47.833 (<0.001)**	**5.469 (0.030)**
Response accuracy	3.267 (0.086)	**10.335 (0.004)**	2.318 (0.144)
Immediate effect (T2 $vs.$ T3)			
Reaction time	**12.079 (0.002)**	**12.332 (0.002)**	4.306 (0.051)
Response accuracy	3.722 (0.068)	0.172 (0.682)	**4.718 (0.042)**

Note: Significant effects ($p < 0.05$) were indicated by the **bold** text.

two sessions exhibited different patterns. The immediate and general effects of mid-task exercise on behavioral performance were analyzed by the two-factor repeated measures ANOVA. For the general effect (i.e., T1 $vs.$ T4) of mid-task exercise, the results of the RT revealed a significant main time effect ($F_{1,20} = 47.833$, $p < 0.001$) and interaction effect ($F_{1,20} = 5.469$, $p = 0.03$) between the two conditions (Table 1). Further post-hoc tests showed that the significant interaction was attributed to the higher RT increment of the *intervention session* ($F_{1,20} = 31.962$, $p < 0.001$) compared to that of the *no-intervention session* ($F_{1,20} = 11.759$, $p = 0.003$). Meanwhile, the response accuracy of the two sessions was significantly decreased ($F_{1,20} = 10.335$, $p = 0.004$) towards the end of the experiment. Furthermore, the investigation on the immediate effect (T2 $vs.$ T3) of RT revealed main session effect ($F_{1,20} = 12.079$, $p = 0.002$) and time effect ($F_{1,20} = 12.332$, $p = 0.002$), while there was a marginal significance level of interaction effect ($F_{1,20} = 4.306$, $p = 0.051$). Regarding the response accuracy, significant interaction ($F_{1,20} = 4.718$, $p = 0.042$) was found, which was attributed to the decreased accuracy in the *no-intervention session* and the increased accuracy in the *intervention session* ($F_{1,20} = 7.127$, $p = 0.015$).

B. Analysis of Networks Metrics

The analysis results of network topological metrics are displayed in Fig.3. For the general effect of the mid-task exercise, a significant time effect of local efficiency ($F_{1,20} = 7.547$, $p = 0.012$) was found in the theta band, manifested as

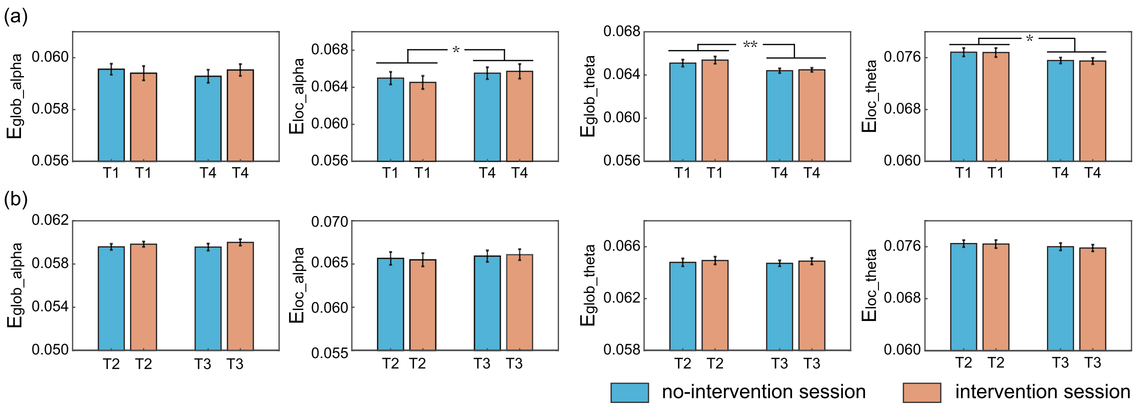

Fig. 3. Post-hoc statistical analyses of global efficiency and local efficiency. Bars represent mean ± standard error. ⋆ represents $p < 0.05$, ⋆⋆ represents $p < 0.01$. T1 and T4 represent the first and last 5-min bins of the PVT respectively, T2 and T3 represent the pre-intervention and post-intervention periods respectively. E_{glob_alpha} is the global efficiency of the alpha band, E_{loc_alpha} is the local efficiency of the alpha band. (a) The general effect of mid-task exercise on network metrics. (b) The immediate effect of mid-task exercise on network metrics.

a decrease at the final period of the experiment. However, regarding the alpha frequency band, the measure of local efficiency was significantly higher ($F_{1,20} = 7.284$, $p = 0.014$) in T4 than that derived in T1. Meanwhile, global efficiency decreased significantly ($F_{1,20} = 8.09$, $p = 0.010$) at the end of the vigilance task in both sessions. Corresponding to the general effect, the immediate effect of the intervention on the network metrics showed no significant difference between the two sessions. Of note, a decreasing trend of global efficiency in the alpha band was shown in the *no-intervention session*, while an increasing trend was exhibited in the *intervention session*.

C. Discriminative Functional Connectivity

State classifications were performed to delve into the changes of FC. The optimal classification accuracy was adopted to obtain discriminative FC regardless of the number of features selected. The acquired number was 80 out of the 3906 features in the *intervention session* after performing general effect classification, and the determined number in the *no-intervention session* was 140 to achieve high classification accuracy. The obtained accuracy was 92.65% ($p < 0.001$) in the *intervention session* and 88.26% ($p < 0.001$) in the *no-intervention session*. Similarly, in the immediate effect classification, the accuracy of 110 features was 88.50% ($p < 0.001$) in the *no-intervention session*, and that in the *intervention session* was 88.66% ($p < 0.001$), using 90 connectivity features.

The selected discriminative features were further evaluated as increased or decreased connectivity, and the detailed distribution was presented in Fig. 4 and Fig. 5. We found more weakened FC in the general effect classification, which accounted for 63.57% (89/140) in the *no-intervention session*, and 58.75% (47/80) in the *intervention session*. Moreover, most of the reduced FC was found in the theta frequency band. The ratio of decreased connectivity in the theta band to the total number of decreased connectivity was 69.66% (62/89) in the *no-intervention session* and 85.11% (40/47) in the *intervention session*. In contrast, enhanced connectivity was mostly located in the alpha rather than the theta band, of which 60.48% (31/51) in the *no-intervention session*,

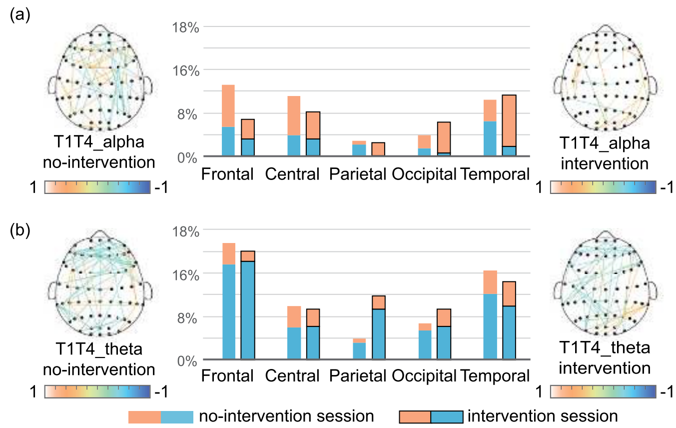

Fig. 4. The selected discriminative features in the general effect classification (i.e., T1 vs. T4). (a) The percentage of increased and decreased FC in the alpha band. The color bars indicate the different weights of FC. The negative values indicate the decreased FC and the positive values indicate the increased FC. (b) The percentage of increased and decreased FC in the theta band. The yellow boxes represent the increased connectivity, and blue boxes represent the decreased connectivity.

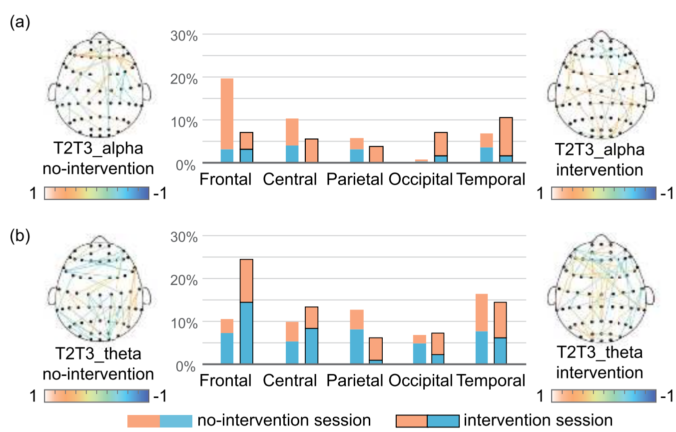

Fig. 5. The selected discriminative features in the immediate effect classification (i.e., T2 vs. T3). (a) The percentage of increased and decreased FC in the alpha band. (b) The percentage of increased and decreased FC in the theta band.

and 63.64% (21/33) in the *intervention session*. However, this phenomenon was not revealed in the immediate effect classification. In addition, both the general and immediate effect classifications found a large proportion of distinct discriminative features between these two sessions. Nonetheless, there were 5 common FCs in the general effect classification, including C5-F5, CP5-FC5, FT8-FP2, AF7-F7, and AF3-FZ. For the investigation of immediate effect, the 12 common features of the two sessions were CP6-P8, FT10-CP6, C1-CP1, F1-FZ, FC6-F4, CP1-PZ, P8-T8, F1-F3, F2-F3, AF8-FC4, AF7-F5, and PO8-T8. To further investigate the distribution of these features on a larger scale, the locations of discriminative features in five brain regions of frontal, central, parietal, occipital, and temporal lobes were analyzed according to the international standard 10-20 system [40]. The results demonstrated that frontal lobe was an important area, as more connectivity was found in this region. Meanwhile, distinct patterns of FC alterations between the two sessions were discovered. As observed, there were more declines in the occipital cortical area of the *no-intervention session*, while the activation level increased in the *intervention session* after performing the exercise intervention. A similar situation also occurred in the parietal region, more enhanced connectivity was found only in the *intervention session*.

IV. Discussion

To investigate the effect of mid-task physical exercise on mental fatigue recovery, we measured behavioral performance and brain network properties in a vigilance task with and without exercise intervention. Firstly, we found the improvement of behavioral performance brought by mid-task exercise, indicating the effectiveness of exercise intervention on mental fatigue. Secondly, the reorganization of brain networks was shown at the end of the task. Meanwhile, the alterations caused by exercise intervention were not detected, which could be explained by the overlapped resource utilization. Thirdly, further state classifications found more reduced FC in both sessions, as well as distinct patterns of FC alterations in distributed brain areas, indicating the altered information processing strategies due to the exercise intervention. These findings were mostly consistent with the hypothesis that the effect of physical exercise intervention would be shown in the behavioral data and brain network analyses. The detailed descriptions are as follows.

A. Behavioral Performance Improvement in the Intervention Session

As expected, the execution of the PVT led to significant increments in RT and decrements in response accuracy, which was consistent with previous studies [26]. Continuous attention to simple and monotonous tasks is high demand, and the essential mental faculty of vigilant attention is necessary to perform tasks. The resource depletion [41] caused by the continuous allocation of attention resources makes it difficult for the subjects to maintain a high level of task performance, which in turn causes mental fatigue, reflected as compromised performance monitoring and inadequate performance adjustments [42]. Fatigue is often accompanied by worsening performance on cognitive tasks, seen in slowed reaction times and increased errors [43], [44], which indicate that fatigue negatively affects attention control ability [45].

The *intervention session* exhibited significant improvement in behavioral performance with the introduction of mid-task exercise. In fact, growing evidence has demonstrated general advantages of exercise in physical and psychological health [46]. A variety of morphological, neurochemical, and electrophysiological alterations in the brain were found in a model of wheel running, which was considered to underlie the behavioral improvements caused by exercise [47]. Nonetheless, the complex relationship between exercise and cognitive function cannot be ignored. Enhanced or impaired cognitive performance during task execution depends on when the task is measured, the type of cognitive tasks, and the type of exercise [48]. Kamiji *et al.* investigated the influence of exercise intensity on cognitive processing and arousal level [49]. The results showed electromyographic reaction time (EMG-RT) after medium-intensity exercise was faster than in a control condition (perform the reaction task) and after low- and high-intensity exercise. Moreover, the P3 (a late positive component of the average evoked potential, with a latency of about 300 msec) amplitude of neuroelectric measures associated with attention resources allocated to tasks was found to increase in moderate-intensity exercise, but decreased in high-intensity exercise [50]. They suggested the fastest EMG-RT and the largest P3 amplitude after medium-intensity exercise were caused by the optimal arousal level. Their previous study revealed the changes in contingent negative variation (CNV), which implied the arousal level was reduced after high-intensity exercise and reached a near optimal level after medium-intensity exercise [50]. Furthermore, some evidences suggested the relationship between exercise-induced arousal and cognitive performance improvement [51], [52]. These may be helpful to explain the decrease in RT and the increase in response accuracy after exercise intervention in this study with the increased neural activation and physiological arousal. In addition, the significant improvement of cognitive performance was shown after a delay following the exercise [53]. During this period, accelerated mental processes and the restoration of memory continue to be promoted by arousal, thus having a relatively prolonged effect on behavior. Researchers suggested the metabolic recovery occurs gradually, and high levels of arousal in the post-exercise period facilitates cognitive function [48], [54]. Thus, it is speculative to consider that the continuous influence of exercise intervention under fatigued conditions may change the original information processing strategy, and achieves long-term benefits of high-level arousal more economically.

B. Network Organization of the Intervention and No-Intervention Sessions

Several studies revealed the disintegration of functional brain connectivity in the state of mental fatigue, such as the higher path length or lower global efficiency [7]. For example, increased path length was observed in a 20-min PVT [22], and significantly reduced global efficiency and increased local efficiency were discovered through a visual oddball task with four successive blocks [55]. These findings imply that brain resources might be reorganized, resulting in the decrements of global integration. Thus, the significantly reduced global efficiency of the two sessions in this paper further verified the network reorganization under mental fatigue. However, no interaction effect of the information transmission efficiency was found between the *intervention* and *no-intervention sessions*. The explanation according to the resource theory could be the domain specific interference [12]. The execution of the vigilance task is associated with a considerable level of stress and workload [56], as well as motor cortical regions, especially the primary motor cortex [57]. A study by Derosière *et al.* [58] on motor neural structures and attention revealed the increment of corticospinal excitability (CSE) and primary motor (M1) activity during the execution of a sustained-attention task. Recently, increased oxygenation in the frontal, parietal-occipital, M1, and supplementary motor regions was shown during driving fatigue through the combination of EEG and functional near-infrared spectroscopy (fNIRS) [59]. Therefore, the execution of PVT and exercise process consume partially overlapped motor mental resources, which may result in the incomplete recovery of related mental resources. Another possible explanation might be the duration of the exercise intervention [7]. Positive effects were observed when the exercise time was no less than 20 min [48], [53]. Thus, longer intervention time is worthy of further study, which may produce a significant influence on network efficiency.

The Pearson correlation coefficients were calculated between the behavioral data (RT and accuracy) and the integrated network metrics (global and local efficiency). Only those statistically significant network metrics were analyzed. However, no significant differences were found in the two sessions. It is speculated that a small number of participants may result in no significant results being observed. Furthermore, the existence of individual differences may be another possible explanation [60]. Significant individual differences of behavioral change were observed, with approximately half the participants showing a decrease and half showing an improvement following the mid-task break [61]. They explained that trait-like psychological mechanisms may underlie these individual differences. Subsequently, interesting results were revealed through analyses of correlations between resting EEG power and reaction time changes, that the significant correlation between RT and upper alpha was observed, while no associations with lower alpha or theta bands. These findings suggest that more careful and thoughtful analyses should be performed in our further study.

C. Differences of Discrimintative Functional Connectivity

To make a further investigation from the perspective of single FC, state classifications were performed. The findings revealed reduced FC was more located in the theta than the alpha band in the general effect classification. Previous studies indicated the changes in theta band seem to be directly related to the deterioration of task performance [20]. Meanwhile, more increased FC was revealed in the alpha band, which may be related to the task-positive networks [62]. Neural activities in these networks, such as the fronto-parietal attention network (FAN), are usually increasing during the execution of cognitive tasks [62]. However, reduced alertness would show up as the task progresses, and the compensatory efforts afforded to the task may increase to maintain performance levels [20]. More importantly, the compensatory efforts of the alpha band might not sufficient to balance the weakened connectivity activity of the theta band. The selected weakened theta connectivity and enhanced alpha connectivity may accordingly implicate the deterioration of performance in vigilance task execution. In addition, the significant decrease in left frontal-parietal connectivity caused by mental fatigue has been reported [22]. In this study, the reduced FC accounted for a large part of the discriminative features obtained in the general effect investigation, which may be the reason for the significant decreases of the brain network efficiency. Using the fMRI technique, Nakagawa *et al.* [63] observed diminished activities that exist in most brain regions, including the frontal, temporal, occipital, and parietal areas. The activities of wide brain areas were demonstrated to be reduced with ongoing mental fatigue, especially in the prefrontal cortex [64]. Similarly, we found the selected features were more located in the frontal area that plays an important role in cognitive control. Of note, regarding the occipital and temporal areas, more reduced FC was chosen in the *no-intervention session*, but there were more enhanced connectivity features in the *intervention session*. Similarly, more increased FC was observed in the parietal region, which only appeared in the immediate effect classification. The increased FC in these regions may play a role in the improvement of behavioral performance. Distinct patterns of FC alterations between the two sessions were also demonstrated, indicating different information processing strategies adopted in the *intervention session*.

D. Future Consideration

In this paper, some factors should be considered when interpreting our results. First, we constructed the FC in sensor space, a number of studies have utilized the source localization approach to investigate the brain network in the source space [21], [22]. Given its theoretical and practical issues [65], we adopted a feasible method to solve the influence of common source and volume conduction [32]. Nonetheless, the cortical space could be further explored to investigate the relationship between cortical areas involved in fatigue recovery. Second, regarding the intervention period, it is worth noting that EEG activity of the rest period was reported to be associated with the behavioral performance in the subsequent vigilant task [61]. In this work, we mainly investigated the general and immediate effects of mid-task exercise intervention on mental fatigue recovery, thus the task periods after exercise intervention were especially analyzed. Complete data should be considered to further investigate the neural mechanism of exercise intervention in view of the insufficient studies on fatigue recovery. Finally, though the aerobic exercise of moderate intensity is demonstrated to be beneficial to attention [15], these investigations were not carried out under mental fatigue. The execution of exercise inevitably brings interruption to the vigilance task, which may contribute to the changes in behavioral data and FC and have an impact on the credibility of the conclusion. Thus, the supplementary rest intervention would be necessary to obtain more convincing results, which will also be considered in future experiments.

V. Conclusion

In this study, we estimated the fatigue recovery effect of mid-task physical exercise using functional brain network and feature classification approaches. The findings revealed that mid-task exercise intervention may change the information processing strategies during task execution, as evidenced by significant improvement of behavioral performance in the *intervention session*, distinct patterns of FC alterations in several brain areas, as well as the distinguishing features between the two sessions. In addition, reduced FC was revealed in distributed brain areas, which may lead to the significantly decreased network efficiency. Moreover, no interaction effect of network metrics could be explained by the overlapped consumption of mental resources between the two sessions. Our findings might contribute to the understanding of the neural mechanisms of exercise intervention and fatigue recovery, and provide new ideas for the safety and efficiency in real-life situations.

Acknowledgment

The authors acknowledge the assistance of Yuqin Han, Qia Hu, and Ran Li for experiment design and data collection.

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