Long-Term Cognitive Tasks Impair the Ability of Resource Allocation in Working Memory: A Study of Time-Frequency Analysis and Event-Related Potentials

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ABSTRACT Long-term cognitive tasks can lead to mental fatigue, which can increase the risk of accidents. P300, theta (4-7 Hz), and alpha (8-13 Hz) power are related to cognitive functions. In this paper, we selected long-term cognitive tasks to induce mental fatigue. Sternberg-WM paradigm was performed before and after fatigue, and EEG data was collected and analyzed. P300 amplitude had no significant difference in the normal state, but significantly reduced with increasing of the workload in parietal region in the fatigue state. This indicated that mental fatigue reduced the allocatable cognitive resources in the high workload. P300 latency had no significant difference between the normal and fatigue state, indicating that mental fatigue had no significant effect on the speed of cognitive resource allocation. Theta power increased significantly with increasing of the workload only in the normal state, indicating that the high workload required more top-down attention resource input to promote memory retrieval. Mental fatigue weakened attention resource input. Alpha power significantly decreased with increasing of the workload only in the fatigue state, indicating that mental fatigue reduced the energy of suppressing irrelevant information interference in the high workload. Long-term cognitive tasks can impair the allocation of cognitive resources, reduce cognitive ability, and lead to behavioral errors in the high workload. P300 can be used as a biomarker for monitoring mental fatigue in the high workload, besides, theta and alpha rhythms can be used as potential targets for neural oscillations regulation.

INDEX TERMS Long-term cognitive tasks, EEG, working memory, Sternberg-WM paradigm, P300, time-frequency analysis.

I. INTRODUCTION

Mental fatigue caused by long-term cognitive tasks is a major health problem in today's society [1]. Grandjean [2] defined mental fatigue as a state in which people show a decline of mental alertness and performance. Long-term mental fatigue can lead to forgetfulness, neurasthenia, depression, and chronic fatigue syndrome [3]. Some studies have shown that mental fatigue can impair cognitive ability [4]. Working memory (WM) is the cognitive center and cognitive basis of human beings [5]. WM supports higher cognitive functions, such as liquid intelligence, decision-making, and learning.

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Whether the decrease of alertness and performance in long-term cognitive tasks is caused by the impairment of WM needs to be further discussed.

At the neurophysiological level, event-related potential (ERP) technology can provide the millisecond time resolution [6], [7], which is suitable for the study of rapid cognitive processes. P300 is an ERP component related to cognitive functions such as attention, decision-making, recognition, and memory [8]. It originates from the activation of the parietal lobe, and reflects a ''top-down'' process of shifting attention to infrequent target stimuli that require motor responses (button presses) or memory updates. Pergher *et al.* [9] found that the P300 amplitude of the elderly attenuated faster in the high workload. P300 amplitude can monitor

cognitive load. The decrease of P300 amplitude is due to the complex multi-component nature of the memory search task, in which the resources needed for the detection and comparison process are "reallocated" or exhausted by the memory rehearsal part of the search task [10]. Therefore, increasing of the workload gradually leads to the decrease of available resources, thereby reducing P300 amplitude to the target stimulus in the search task [11]. In the study of patients with depression [12] and cognitive impairment [13], P300 amplitude was lower than that of the normal people. In terms of latency, the latency is proportional to the speed of stimulus evaluation, and is sensitive to task processing. P300 latency varies with individual differences in cognitive ability [14]. The study of mild brain injury found that [15], [16], the prolongation of P300 latency reflected that brain injury slowed down the information processing in the stages of stimulus assessment and decision-making.

P300 is a complex ERP component, which involves the source of generation, waveforms, and functional reactivity. Time-frequency analysis helps to reveal partly or fully processes taking place in the P300 latency range, and these processes are indistinguishable in the ERPs analyzed only in the time-domain. Theta (4-7 Hz) band in the frontal region is closely related to the top-down execution control [17], and is related to the maintenance activity of sample stimulation. The power of theta band in the frontal midline increases with increasing of attention resource input [18]. Also, theta band is related to the central executive functions of WM, which can promote memory retrieval. Alpha (8-13 Hz) rhythm is the first major rhythm found in scalp electroencephalogram (EEG). It plays an important role in WM, mainly to inhibit the interference of irrelevant stimuli. Alpha loading effect is often found in the posterior part of the cerebral cortex, including the occipital and parietal-occipital sulcus. Alpha loading effect is not clear. In different experiments, alpha rhythm presents different loading effect. Some studies have shown that the decrease of alpha is related to the increase of arousal, distribution, and workload in visual tasks [19]. While others have found that the alpha rhythm increases with the number of WM items [20], to protect WM target information from irrelevant stimuli [21].

Through the Sternberg-WM paradigm, we recorded the EEG signals of WM before and after mental fatigue. We expect to explore the impact of long-term cognitive tasks on resource allocation under different workloads through P300 and time-frequency analysis. We expect the behavioral performance to decline after long-term cognitive tasks in the high workload. For electrophysiological indicators, we expect long-term cognitive tasks to reduce P300 amplitude and alpha power, and increase theta power in the high workload.

II. MATERIALS AND METHODS
A. PARTICIPANTS
We recruited 25 college students (years: 23.47±1.16), including 17 males and 8 females. All participants were

right-handed and had a normal or corrected-to-normal vision. All participants had no history of neurological disorder or the use of psychoactive medications. In order to avoid curiosity and maladjustment on the day of the experiment, participants were required to make an appointment to practice the experiment before the experiment. Besides, all participants were informed to ensure enough sleep and forbid drinking the day before the experiment. This study was approved by the Ethics Committee of Hebei University of Technology. Each subject signed an informed consent form before the experiment.

B. TASK DESIGN
The experiment was conducted in a quiet room. The whole experimental procedure is shown in Fig. 1, which consist of three sections, including long-term cognitive tasks and Sternberg-WM paradigm for pre-test and post-test respectively. Before and after the long-term cognitive tasks, participants were required to score Karolinska sleepiness scale (KSS) [22] (1 means extremely alert, 9 means extremely sleepy and unable to stay awake). The behavioral performance and EEG during Sternberg-WM tasks were recorded.

1) STERNBERG-WM PARADIGM
The modified Sternberg-WM paradigm was used to test the performance of WM. Stimulus was presented for 2000 ms, probe item was presented for 2000 ms after the 10 s maintenance period. We designed three different workloads, the workload was marked as size2 if it was two letters, size4 if it was four letters, and size6 if it was six letters. Three kinds of workload appeared randomly and had equal probability. The total duration of each workload was 10 minutes. The target (probe item appeared in the stimulus) pressed the "←" button, and the non-target (probe item did not appear in the stimulus) pressed the "→" button. Among them, target and non-target appeared randomly, and the probability was equal.

2) LONG-TERM COGNITIVE TASKS
The adaptive N-Back experiment was chosen as long-term cognitive tasks, which determined whether the current stimulus matched the two or three items presented before. The match pressed the "←" button, and the mismatch pressed the "→" button. The stimulus presented 500 ms, and the stimulus interval was 2500 ms. The choice of 2-back or 3-back was based on individual mental conditions. When the accuracy of 3-back was more than 85%, 3-back was chosen, otherwise, 2-back was chosen. When KSS reached about 8, long-term cognitive tasks ended.

C. EEG ACQUISITION AND ANALYSIS
The EEG data was recorded by Neuroscan system using 64 active Ag/AgCl electrodes mounted in an elastic cap with a standard 10-20 system. The electrode impedance was less than 5 $K\Omega$. The sampling frequency of EEG data was 1000 Hz. The recorded EEG was re-referenced offline to the average of the bilateral mastoid, and band-pass filtered in the 0.1-30 Hz range. Stimulus-locked data was cut into
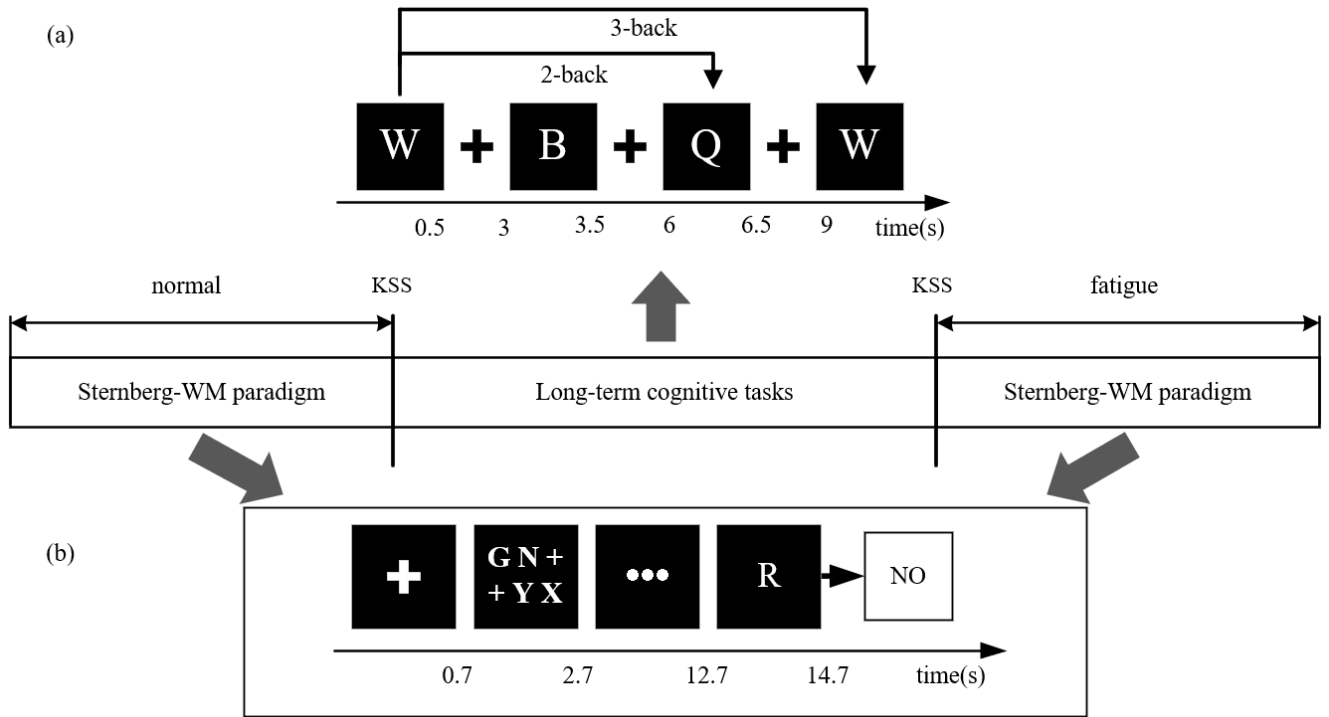
(a)

(b)

FIGURE 1. The experimental procedure. (a) Long-term cognitive tasks. (b) The modified Sternberg-WM paradigm.

epochs starting from 200 ms pre-till 800 ms post-stimulus onset. Baseline correction was performed by subtracting the average of the 200 ms pre-stimulus onset activity from the 800 ms post-stimulus onset activity. The epochs were down-sampled to 256 Hz. Eye blinks were identified by independent component analysis (ICA) and eliminated. Epochs containing muscle artifacts or saccades, identified through ICA and visual inspection, were rejected. Finally, the processed data was stored for ERP component detection. P300 was measured as the maximum amplitudes at Fz, Cz, and Pz from intervals of 250-450 ms post-stimulus.

D. MULTI-TAPER METHOD

The Multi-taper method was used for time-frequency analysis, in which the theta band was defined as the 4-7 Hz, alpha band was defined as the 8-13 Hz. Power was the average of each time period and frequency band. Multi-taper method [23] is a spectral analysis method with low variance and high resolution, which is especially suitable for signal diagnosis and analysis in the background of short sequence and high noise. It multiplies the time histories by a set of orthogonal tapers to form several single-taper periodograms to balance the low variance and low deviation of spectral estimation. Then the multi-tapered spectrum is constructed by the weighted sum of these single-taper periodograms. Multiple tapers can reduce spectral leakage. More numbers of tapers minimize the variance in the spectral estimates.

The multi-taper spectral estimate is given by,

$$\hat{P}_{xx}^{(MTM)} = 1/K \sum_{K=0}^{K-1} \hat{P}_{xx}^{(k)}(\omega) \qquad (1)$$

where,

$$\hat{P}_{xx}^{(k)}(\omega) = 1/N \left| \sum_{n=0}^{N-1} x(n)h_k(n)e^{-j\omega n} \right|^2 \qquad (2)$$

where, N is the data length, the window function is $\{h_k(n), 0 \leq k \leq K - 1\}$. If the estimates $\hat{P}_{xx}^{(k)}(\omega)$ are uncorrelated, the variance of the multitaper estimate would be scaled down by a factor of K. To ensure approximate uncorrelatedness of the tapered estimates $\hat{P}_{xx}^{(k)}(\omega)$, the tapers must be orthonormal.

$$\sum_{k=0}^{K-1} h_k^i h_k^j = \delta_{ij} \qquad (3)$$

E. STATISTICAL ANALYSIS

The paired t-test was used to compare KSS. The two-way repeated measures analysis of variance (ANOVA) was used to analyze the reaction times (RTs) and accuracy, the within-subject factors included the state (normal, fatigue) and the workload (size2, size4, size6). The three-way repeated measures ANOVA was used to analyze the amplitude and latency of P300, the within-subject factors included the state (normal, fatigue), electrode position (Fz, Cz, Pz), and the workload (size2, size4, size6). The two-way repeated measures

ANOVA was used to analyze the power of alpha and theta, the within-subject factors included the state (normal, fatigue) and the workload (size2, size4, size6). The simple effect test was carried out when the interaction effect was significant. The α level of all statistical analysis was 0.05. Greenhouse-Geisser correction was applied where appropriate to correct for violations of the spherical assumption. All statistical comparisons were performed with SPSS26.0.

III. RESULTS

A. KSS RESULTS

In the normal state, the mean value of KSS was 3.30 ± 0.34. After long-term cognitive tasks, the mean value of KSS was 7.87 ± 0.33, which was significantly higher than that in the normal state ($P < 0.001$). The results showed that the subjects reached the state of mental fatigue at the level of self-feeling.
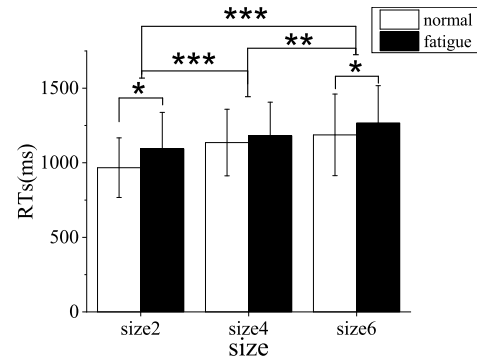
B. BEHAVIORAL RESULTS

To assess changes in behavioral performance after long-term cognitive tasks, we examined RTs and accuracy (Fig. 2). The RTs in the fatigue state were significantly longer than that in the normal state ($F = 8.83$, $P < 0.01$). RTs increased significantly with increasing of the workload, whatever state ($F = 30.37$, $P < 0.001$). The interaction effect between the workload and the state was significant, and the RTs were longer under the high workload in the fatigue state ($F = 3.42$, $P < 0.05$). The accuracy in the fatigue state was significantly lower than that in the normal state ($F = 4.87$, $P < 0.05$). With increasing of the workload, accuracy significantly decreased ($F = 22.58$, $P < 0.001$).

C. P300 RESULTS

In the normal state, P300 amplitude and latency had no significant main effect of the workload, but had a significant main effect of the electrode position (amplitude: $F = 21.94$, $P < 0.001$; latency: $F = 6.70$, $P < 0.01$). The amplitude and latency in Fz, Cz, and Pz increased successively. The interaction effect between the workload and the electrode position was significant ($F = 2.88$, $P < 0.05$). The results of simple effect showed that, significant difference was found between all electrode positions ($F = 7.26$, $P < 0.05$) when the workload was size2, and significant difference was found between all electrode positions except Cz and Pz ($F = 20.51$, $P < 0.01$) when the workload was size4, however, significant difference was only found between Fz and Pz ($F = 4.21$, $P < 0.05$) when the workload was size6.

In the fatigue state, P300 amplitude had a significant main effect of the workload ($F = 4.18$, $P < 0.05$) and electrode position ($F = 26.60$, $P < 0.001$). P300 amplitude decreased with increasing of the workload in Pz electrode, and increased successively in Fz, Cz, and Pz. P300 latency had no significant main effect of the workload, but there was a significant main effect of the electrode position ($F = 5.93$, $P < 0.05$). The latency successively increased in Fz, Cz and Pz. The P300 waveforms and amplitude are shown in Fig. 3, 4.


(a)
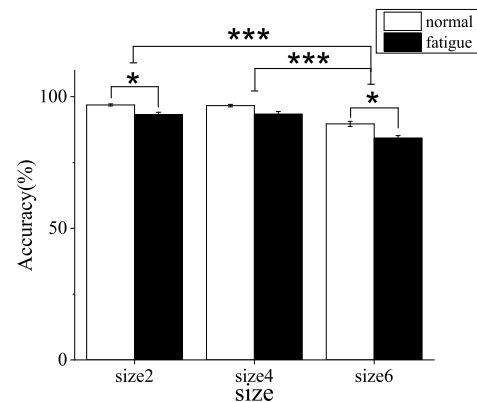
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FIGURE 2. The behavioral results. (a) The results of RTs. (b) The results of accuracy. *$P < 0.05$, **$P < 0.01$, ***$P < 0.001$.

D. TIME-FREQUENCY ANALYSIS

In addition to time-domain analysis, we also carried out time-frequency analysis. We found significant differences in alpha of the frontal and theta of the parietal. Fig. 5 shows the average time-frequency analysis of all participants before and after fatigue. For theta band, there was a significant main effect of the state ($F = 10.12$, $P < 0.01$), which significantly decreased in the fatigue state. Under the factor of workload, it significantly increased with increasing of the workload in the normal state ($F = 4.07$, $P < 0.05$), but there was no significant difference in the fatigue state. For alpha band, there was no significant main effect of the state. Besides, there was no significant difference of the workload in the normal state, but the power of size6 was significantly lower than size2 in the fatigue state ($F = 4.51$, $P < 0.05$).

IV. DISCUSSION

In this study, we chose Sternberg-WM paradigm to study the effects of long-term cognitive tasks on cognitive resource allocation in the high workload. Long-term cognitive tasks had significant effects on EEG in time-domain and frequency-domain in the high workload. P300 amplitude and alpha power significantly decreased, indicating that
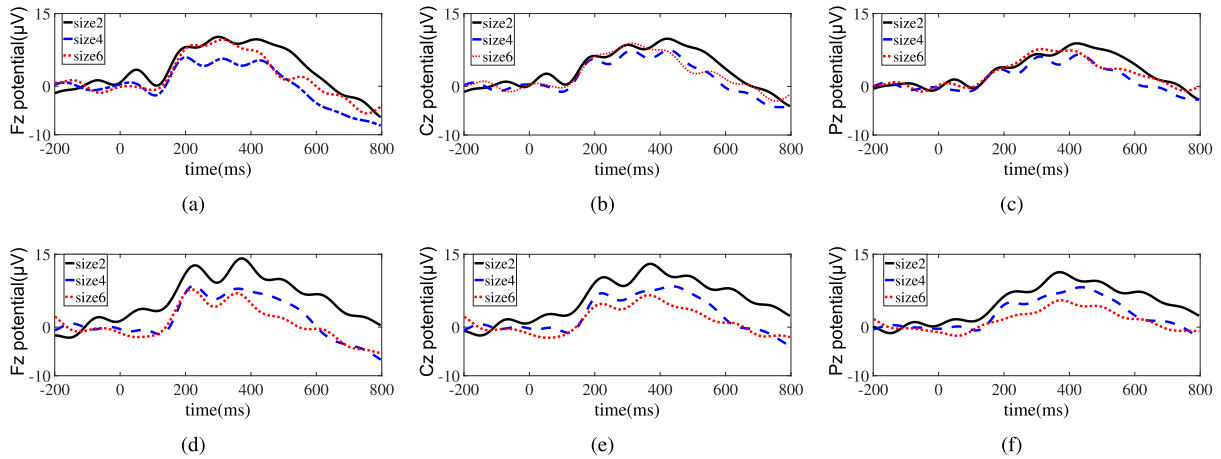
FIGURE 3. Grand-averaged P300 waveforms. (a), (b), (c): P300 waveforms at Fz, Cz, Pz electrodes in the normal state. (d), (e), (f): P300 waveforms at Fz, Cz, Pz electrodes in the fatigue state after long-term cognitive tasks.
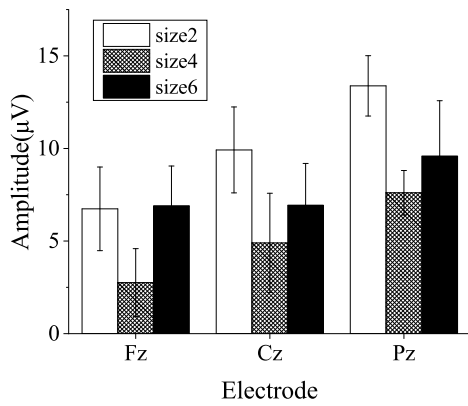

(a)
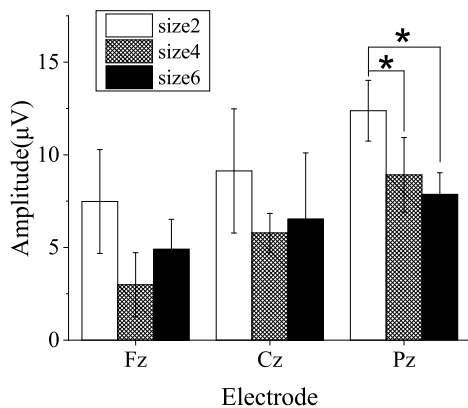
(b)

FIGURE 4. The amplitude of P300. (a) The amplitude of P300 in the normal state. (b) The amplitude of P300 in fatigue state. *P < 0.05.

long-term cognitive tasks weakened the functions of inhibiting irrelevant stimuli and reduced allocatable resources. Theta power significantly decreased. It showed that long-term cognitive tasks reduced attention resource input and ultimately weakened resource allocation ability.

According to the results of behavioral analysis, after long-term cognitive tasks, RTs increased and accuracy decreased with increasing of the workload. Long-term cognitive tasks hindered the smooth progress of WM in the high workload.

P300 is an important index to reflect the cognitive demands of WM. Its amplitude [24] reflects the allocation and updating ability of cognitive resources in WM. P300 latency is related to the speed of classifying and distinguishing stimulus that may occur in the process of memory updating, thus it can be used as an objective indicator of the processing speed of the central nervous system in the process of WM [25]. In this study, P300 amplitude had no significant difference in the normal state. After long-term cognitive tasks, P300 amplitude significantly decreased with increasing of the workload in the parietal region, indicating that long-term cognitive tasks weakened the ability for allocation and renewal of cognitive resources in the high workload. This may be the reason for the decrease in the accuracy of keystrokes. This is also in line with the inhibition hypothesis [26]. High cognitive needs tasks limit the level of attention resources to resist inhibition, which results in a smaller P300 component. The parietal cortex is considered to be the key brain area for the representation storage of WM [27], [28]. The activity of the inferior parietal sulcus is sensitive to the number of objects, while the activity of the superior parietal sulcus is more sensitive to the complexity of objects [29]. This may indicate that, long-term cognitive tasks mainly affect the activity of the inferior parietal sulcus in the high workload, although WM has varying degrees of impact on the frontal and parietal network. P300 latency had no significant difference in both the two states, indicating that when the workload did not exceed the subjects' cognitive ability, the higher workload had no significant effect on the decision-making speed of brain [30]. Or the experiment was too simple for the participants, which led to the ceiling effect.

Theta rhythm is closely related to top-down executive functions, such as attention. The power of theta band is related to the input of attention resources, which promotes memory retrieval by devoting more attention resources [31]. In the
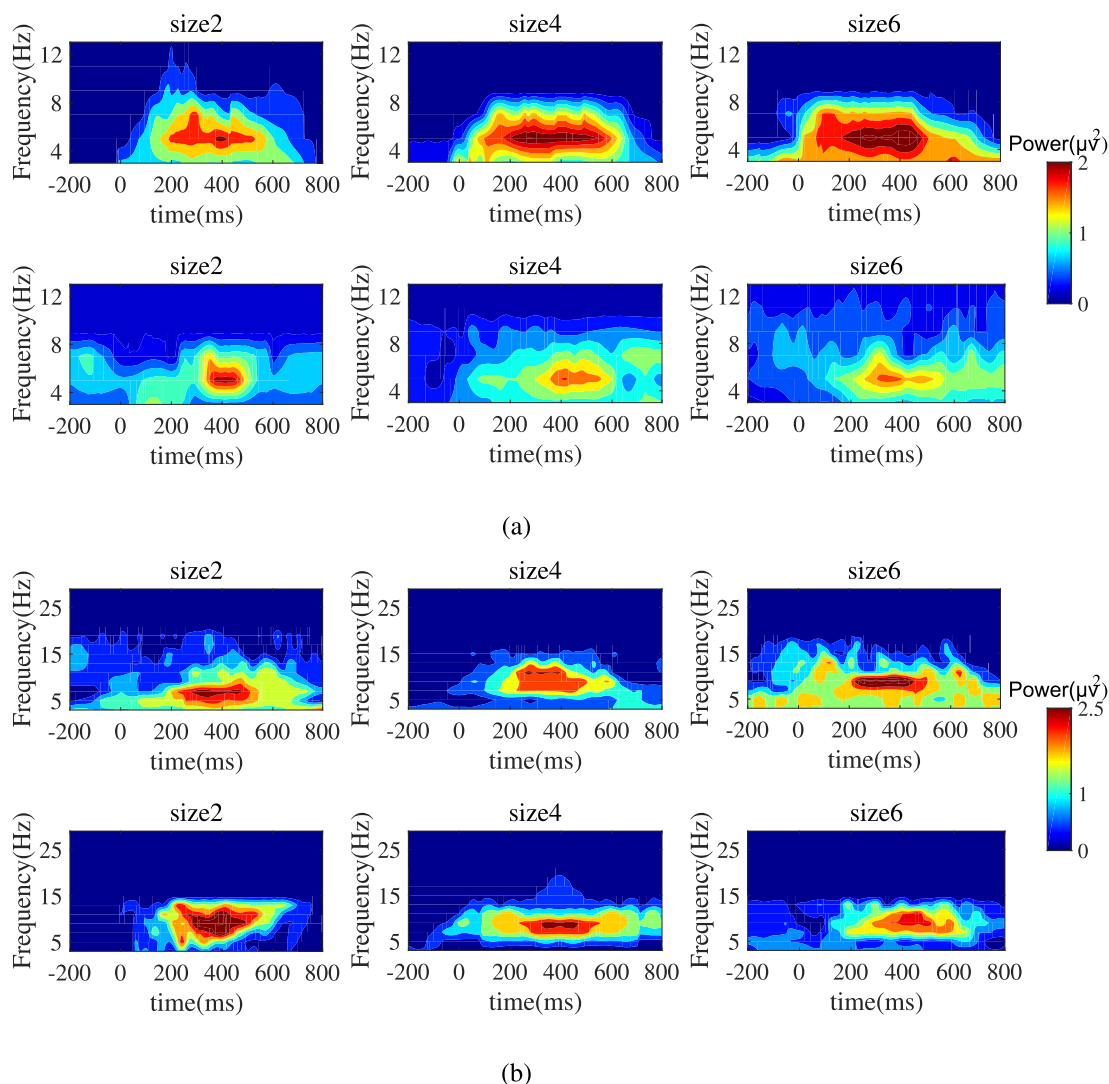
FIGURE 5. Comparison of time-frequency analysis before and after fatigue. (a)Time-frequency analysis of theta band in the frontal. The top is the time-frequency analysis in the normal state, and the bottom is the time-frequency analysis in the fatigue state. (b)Time-frequency analysis of alpha band in the parietal. The top is the time-frequency analysis in the normal state, and the bottom is the time-frequency analysis in the fatigue state.

normal state, the power of theta band increased with increasing of the workload. In this condition, theta rhythm was gradually activated. Therefore, cognitive ability was enhanced, and the input of attention resources was increased. This may explain the growth of RTs with increasing of the workload in behavioral results. The power of theta band significantly decreased in the fatigue state, but there was no significant change in the workload factor. Long-term cognitive tasks made the input of attention resources cannot increase with increasing of the workload, which caused the weakening of top-down execution ability. After long-term cognitive tasks, participants were unable to retrieve memory more effectively in the high workload. This may reduce the allocatable cognitive resources, which may be the reason for the increase of RTs after mental fatigue.

Alpha rhythm is associated with emptying, default mode brain activity, and cortical inhibition [32]. According to the alpha inhibition hypothesis [33], low alpha activity reflects active neuronal processing, that is, lower alpha bands are more likely to reflect attention task needs. The power of alpha band had no significant difference in the normal state, but decreased with increasing of the workload in the fatigue state. The attention and cognitive needs increased with increasing of the workload in the fatigue state, so that fewer resources were used to suppress the interference of irrelevant information. Ultimately, the cognitive resource allocation ability was affected. This may be the reason for the decrease in the accuracy after long-term cognitive tasks.

V. CONCLUSION
Our study reveales that in the high workload, long-term cognitive tasks can damage the ability to allocate cognitive resources, and reduce cognitive ability. People show an increase in behavioral errors in appearance. P300 can be used as a biomarker to monitor mental fatigue in the high workload. In addition, electromagnetic stimulation technique has a

good effect on regulating neurological problems [34]. In regulating mental fatigue caused by long-term cognitive tasks in the high workload conditions, theta and alpha rhythms can be used as potential targets for neural oscillations regulation. This research can be considered for fatigue and workload monitoring during operation of brain-computer interfaces in the future.

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