EEG Correlates of Sustained Attention Variability during Discrete Multi-finger Force Control Tasks

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***Abstract*—The neurophysiological characteristics of sustained attention states are unclear in discrete multi-finger force control tasks. In this article, we developed an immersive visuo-haptic task for conducting stimulus-response measurements. Visual cues were randomly provided to signify the required amplitude and tolerance of fingertip force. Participants were required to respond to the visual cues by pressing force transducers using their fingertips. Response time variation was taken as a behavioral measure of sustained attention states during the task. 50% low-variability trials were classified as the optimal state and the other high-variability trials were classified as the suboptimal state using z-scoring over time. A 64-channel electroencephalogram (EEG) acquisition system was used to collect brain activities during the tasks. The haptics-elicited potential amplitude at 20 $\sim$ 40 ms in latency and over the frontal-central region significantly decreased in the optimal state. Furthermore, the alpha-band power in the spectra of 8 $\sim$ 13 Hz was significantly suppressed in the frontal-central, right temporal, and parietal regions in the optimal state. Taken together, we have identified neuroelectrophysiological features that were associated with sustained attention during multi-finger force control tasks, which would be potentially used in the development of closed-loop attention detection and training systems exploiting haptic interaction.**

***Index Terms*—Sustained attention, EEG, multi-finger force control, speed-accuracy tradeoff, electrophysiological feature.**

I. Introduction

SUSTAINED attention is the cognitive ability to consistently maintain attention on an elementary, even dull, task over long periods [1]–[3]. The ability to sustain attention is limited but critical to everyday tasks with real-world implications that impact academic outcomes, safety, social communication, and mental health [4]–[6]. For example, in agreement with previous research on railway accidents, failed sustained attention was the most salient contributing human factor across all incident types, particularly inattentiveness to railway signals [7]. Given the importance of sustained attention, cognitive-behavioral training for sustained attention enhancement had been a research hotspot in the field of cognitive neuroplasticity and had great potential for the treatment of attention deficit hyperactivity disorder (ADHD), mild cognitive impairment (MCI), and other neurological disorders of attention [8], [9]. Therefore, it is promising to construct an effective sustained attention training method using multimodality interaction tasks in a home-based environment [10].

However, the majority of existing studies revealing the physiological mechanisms of attention enhancement were conducted with visual and auditory interaction paradigms [11], [12]. The mechanisms of attention enhancement based on immersive visuo-haptic interaction have been less studied. Neuro-cognitive basis of haptic perception showed that tactile receptors in the human hand send feedback information about surface contact properties to the central nervous system [13]. This feedback is preprocessed in the primary somatosensory area and subsequently engage the attentional network in the brain. The advantages of the fingers over other body parts include sensitive haptic perception and fine muscle control capabilities. High-precision force control of fingertip or dexterous operation of multi-finger coordination is closely related to the allocation of attention resources. Only a few attention-related studies were carried out through force feedback devices [14], [15]. Unveiling the sustained attention enhancement mechanism using haptic interaction could lay the foundation for further studies in closed-loop attention training systems with neurofeedback, and ultimately enable the haptic modality as an additional channel for neurocognitive rehabilitation besides visual and auditory modalities.

Our long-term goal is to understand the cognitive neural mechanism of haptic interaction and develop a neural feedback-assisted attention training and neurorehabilitation paradigm using fingertip force control in immersive virtual environments. As a follow-up work of our previous studies [14]–[16], Peng et al. [17] demonstrated that the attention performance of trainees in two typical attention tests was improved through longitudinal training with a visuo-haptic attention training game via fine force control. Whereas, the neurophysiological dynamics related to the attention improvement during the proposed training were not clear yet. The

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electroencephalographic (EEG) markers of sustained attention have not been fully exploited during visuo-haptic finger force control tasks within an immersive virtual environment.

Thus, the critical question in the current study is what electroencephalographic (EEG) features are correlated with sustained attention states during the fingertip force control task in an immersive virtual reality (VR) environment. The work presented in this paper acts as one of the key steps to reveal the behavioral and neurophysiological markers of sustained attention in visuo-haptic multi-finger force control tasks. Based on the visuo-haptic attention training game introduced in our earlier work [17], the EEG signals were collected when performing the discrete fingertip force control task. Inspired by the methodologies outlined in previous studies [11], [18], we analyzed trial-by-trial response time variabilities in the dichotomous behavioral division to classify trials into the low- or high-variability states indicating two sustained attentional states: optimal and suboptimal states, respectively. Based on these two epochs, event-related potential (ERP) and power spectral analyses were conducted to extract EEG biomarkers significantly differing in the two states of sustained attention. The identified sustained attention biomarkers could support an adaptive closed-loop neurofeedback attention training system for augmented cognition [19].

The main contributions of this paper are as follows: First, we designed visuo-haptic multi-finger force control tasks that revealed two neuroelectrophysiological features significantly correlated with sustained attention. Second, we proposed a VR-EEG measurement platform integrating head-mounted display (HMD), providing immersive 3-D virtual reality environments and 64-channel EEG data acquisition over the whole scalp of users. These contributions laid an essential technical foundation for further developing attention training systems using immersive visuo-haptic interaction tasks.

II. Related Works

Neurohaptics involves the understanding of how touch and its underlying brain functions work as well as its controlling cognitive interaction via brain-machine-interface [20]. Haptic interaction involving finger force was ubiquitous in the real world, thus it was essential to uncover the neural underpinnings of brain activities in the haptic interaction [19]. In recent years, the potential of haptics in attentional enhancement has attracted more and more attention of cognitive neuroscientists in addition to visual and auditory interaction [21]. However, the assessment of attention has been the primary issue when conducting attention-related research. In psychological science, there was far from a wide consensus on the gold standard of inattention, although it had been researched for more than a century [22]. It was still a challenge to reliably monitor the attentional state of a user by neurophysiological measurements, especially in real-world learning and training environments [19].

The most common method was based on self-reported data from probe questions or behavioral performance. Self-report was a necessary subjective measure because brain wandering, by definition, was unpredictable and implicit. After randomly inserting probe questions into the tasks of interest, participants were asked to report their thoughts and feelings while performing the task. Mind-wandering was typically measured experimentally by the self-report whereby distractive feelings were marked in these reported discrete time points [23]. However, an obvious drawback of the self-report methodology was that probes would interrupt the ongoing train of thought, causing unwanted interference [23]. For a task with the aim of further application in complex real-world scenarios, the self-report methodology was not appropriate due to the interruption. Therefore, a new trend in sustained attention research was to detect the performance of a task over a long period of time to explain individual fluctuations in the overall ability to maintain stable task performance [11], [24].

Many methods had been developed for examining within-subjects response time variability over time, based on the observation of the behavior of ADHD patients [25]. A typical way to measure attentional fluctuations during sustained attention was a behavioral measure of moment-to-moment performance, e.g., sustained attention to response task (SART) [26]. The significant change in trial-to-trial reaction time had been considered as an important indicator of attention performance [27]. The abnormally slow response time was conceptualized as a lack of preparation for tasks or a decrease in attention, while the abnormally fast response time was considered as an early or routine response, which was related to the failure of attentive control and response inhibition [28]. The sustainability of attention control could not be fully captured just by checking the accuracy and speed of response [27]. SART-like continuous performance tests (CPT) were more sensitive to the instantaneous change of the attentional state than classic vigilance tasks, while they often failed to elicit performance decrements in healthy individuals [11]. Traditional findings demonstrated that easier tasks could sometimes result in greater vigilance decrements, besides the demonstrable role of motivation in sustaining attention had cast doubt on this strict resource depletion model [26]. Although typical psychological lab tasks used for the behavioral metric of sustained attention were more convincing, they were far from attractive and practical daily training tasks [29].

In different practical tasks, a modified method derived from the classical paradigm is necessary for sustained attention measurement even if it may not be widely accepted in a short time [24]. Aiming at detecting vigilance decrements by moment-to-moment response time (RT) fluctuations, Rosenberg *et al.* [27], [30] introduced a novel gradual-onset continuous performance task (gradCPT) with 20 scene images to more adequately tax sustained attention in a short period using frequent overt responses. According to a dichotomous analysis, performance fluctuations were divided into low- or high-variability epochs by the median z-score. Sustained attention was illustrated to fluctuate between "in the zones" (periods of response stability, optimal attention state) and "out of the zones" (periods of instability, suboptimal attention state) [2], [11]. Using fMRI in the gradCPT, Esterman et al. [11], [26] further proposed two neural markers for two states of sustained attention, respectively. Specifically, an optimal state (in the zones) characterized by higher default mode network (DMN) activity was stable and less error-prone for responses. Moreover, a less optimal state (out of the zones) relying on activity in dorsal attention network (DAN) regions was more effortful for sustained performance. These studies provided referable methodologies for the current study to identify behavioral-neural features correlated to sustained attention in haptic interaction.

Throughout the literature, it is common to firstly explore neural markers for predicting trial-to-trial attentional states in pure visual or audio tasks, e.g., the Stroop task [31], attention network test (ANT) [32], and continuous performance tasks (CPT) [33]. The EEG markers were widely taken as features to determine someone's mind-wandering state online [23]. The EEG biomarkers in sustained attention to response task (SART) and a visual search task were studied to classify the real-time attentional state as either mind-wandering or on-task [23]. The founded EEG biomarkers included single-trial ERPs (e.g., P1, N1, and P3) and the power and coherence in the theta and alpha bands. Recent human imaging studies demonstrated that activation of frontal and parietal cortical areas was associated with sustained attention performance [34]. With an oscillatory model of sustained attention, Clayton et al. [35] argued that sustained attention relied on cognitive monitoring and cognitive control functions mediated by frontomedial theta oscillations. Ko et al. [36] found that the delta and theta power of the occipital lobe increased during a sustained attention task in the real classroom environment, while the beta power of the occipital lobe and temporal lobe decreased with the increase of response time. Oscillatory activity in the alpha band was proposed to act a pivotal part in the engagement and disengagement of sensory areas depending on task demands [18]. Although the alpha activity was another useful index of task performance, it varied among studies [37]. These findings inspired us to identify EEG biomarkers of sustained attention in fine force control tasks using fingers.

III. Materials and Methods

A. Experimental Apparatus

The current experimental apparatus consisted of two subsystems: the fingertip force control system and the 64-channel EEG signal acquisition system, as shown in Fig. 1. The fingertip force control system was developed in Unity 3D (Unity Technologies, Brighton, UK), and was specially modified based on the previous experimental system [17]. The present settings kept its original design as much as possible to make our findings applicable directly in future works. To ensure the quality of each electrode signal from the EEG acquisition system, users would be instructed to actively adapt their heads to the head-mounted display (HMD) fixed on the edge of the front desk. The original hardware configuration of the Oculus HMD (Oculus Rift CV1, Oculus Inc., Saint Louis, MO, USA) was specially modified by removing the binding components that hindered the wearing of the 64-channel electrode cap. Moreover, an in-ear soundproof earplug was added to isolate the external noise.

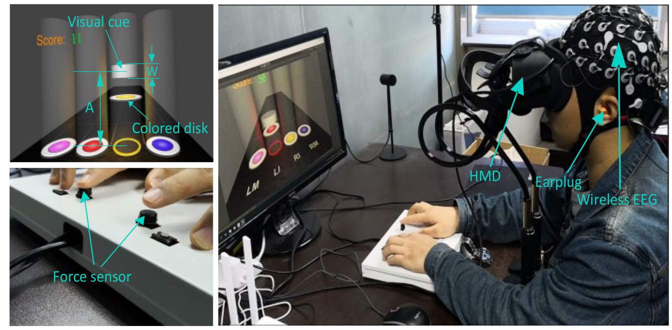

Fig. 1. Components of the prototype and experimental scenario. In a trial, **A** denoted the required force for fingertip pressing, and **W** denoted the allowed tolerance for fingertip force control. HMD denoted the head-mounted display.

There were four unique features in the design scheme of the current experimental platform contrasted with the previous experimental settings. First, the HMD providing immersive virtual reality (VR) environments was fixed on the desk in front of the participants. Therefore, the possible EEG artifacts caused by the HMD binding and head movements were avoided when the EEG cap and the VR-HMD were worn on one user simultaneously. Second, only the central two disks (the red and yellow disks) were activated for the index fingers of both hands, and the others were deactivated to eliminate visuo-spatial perception differences resulting from cues near the edge of the visual field in the immobile HMD. Third, the required amplitude and tolerance preset for fingertip force control remained unchanged in all trials to exclude the response time variabilities resulting from different task difficulties. Fourth, all visual feedback animations were no longer adopted to avoid nontarget task-irrelevant brain responses. No explicit hints were provided for the change of required force and tolerance in an upcoming cue. Users needed to engage themselves in timely responses to the cue with finger force control.

The main hardware components of the EEG signal acquisition system included a stretchable electrode cap containing 64 electrodes in standard 10-20 system positions, NSW364 wireless amplifier (NSW364, Neuracle, Changzhou, China), a customized router, and a trigger box for multi-parameter synchronization. Neural electrical activities were collected with the electrode cap. The impedance of the electrodes was calibrated under 5 kΩ using NaCl-based conductive gel [38]. EEG signals were amplified by a 64-channel wireless EEG amplifier with a sampling rate of 1000 Hz, and recorded online referentially against the CPz electrode by a customed toolbox developed in the MATLAB programming language (MathWorks, Inc., Natick, MA, United States). The immersive VR environment programming was synchronously communicated with the trigger box via a serial communication protocol. Consequently, event times were automatically documented with markers in the continuous EEG data files for every visual cue (marker-1 shown in Fig. 2) and haptic reaction triggered by a finger force exceeding 0.2 N (marker-2 shown in Fig. 2).

B. Discrete Fingertip Force Control Task

The fast-paced stimulus-response force control task in previous studies continued to be used in the current experiment

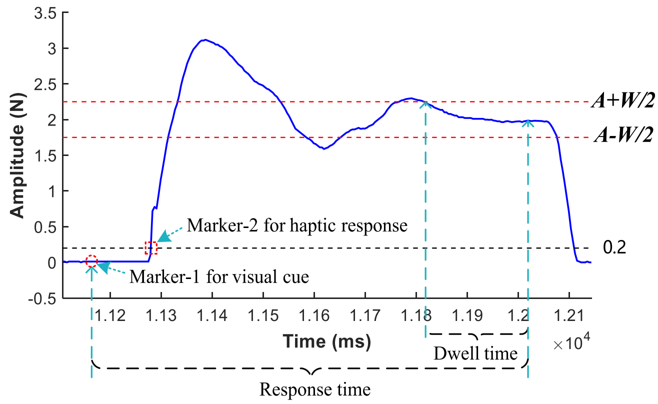

Fig. 2. The real fingertip pressing force with respect to the required amplitude and tolerance in a trial. Correspondingly, the colored disk was over, within, and below the visual cue, respectively.

[17]. As shown in Fig. 1, the height and thickness of the visual cue represented the required fingertip force control requirement with an amplitude $\boldsymbol{A}$ of 2 N and a tolerance $\boldsymbol{W}$ of 0.5 N. The real fingertip pressing force F_{R} was mapped with the height of a corresponding colored disk. Fig. 2 illustrated the amplitude variation of F_{R} in a trial. According to the logical relation among F_{R}, $\boldsymbol{A}$ and $\boldsymbol{W}$, there were three relative spatial distances between the colored disk and the visual cue. For example, if F_{R} entered within the required range, the colored disk would overlap with the thick grey slice. When a visual cue randomly popped up in the cylinder labeled as "LI" or "RI", participants were required to accurately select the assigned fingertip and control its key-pressing force as quickly as possible. To complete a finger force control reaction, a player had to move the colored disk into the visual cue and keep it inside the visual cue for a "dwell time" (T_{D}). The visual cue would disappear once the T_{D} exceeded a predefined threshold time of 200 ms. If the colored disk jumped out of the visual cue in a certain trial, the player needed to adjust his/her key-pressing force immediately to enter the visual cue again until succeeded in this trial. A total of 121 stimulus-response constituted a session. The fingertip force control task consisted of three sessions.

In each trial, the assignment of two index fingers was randomized across the trials. As shown in Fig. 2, the RT was defined as the time taken from the appearance of a visual cue to the completion of force control during one trial. A trial would be successful if the player completed the force control reaction within an allowable response time of 5 s, and he or she would get a score once as a timely reward. Otherwise, this trial would be a failure and no score would be rewarded. After finishing a reaction, the responding finger had to be lifted completely to prepare for the next trial. All players were automatically ranked according to their reaction efficiencies defined in the earlier study [17]. Eight candidates who performed best would be presented on the screen at the end of each session. Therefore, the player would know his/her relative performance among all competitors who were in this task, motivating everyone to perform better in the next session.

C. Participants

A total of 17 volunteers (age range 19 $\sim$ 25 years; mean, 21.94 years; SD, 1.64 years; 5 females) were recruited from Beihang University and the surrounding community in this study. They all reported normal or corrected-to-normal vision acuity and were right-handed in the light of their preferential use of the hand during daily activities such as writing, drawing, and eating. None of the participants had a previous history of neuropathies, traumas to the upper limbs, or long-term involvement in hand or finger activities such as typing and playing musical instruments. The research was conducted following the declaration of Helsinki. All participants provided their written informed consent before the experiment and were informed of their rights to discontinue their participation at any time. Taking the effect of monetary reward on the engagement into consideration [39], some participants could receive a bonus ranging from ¥ 25 to ¥ 200 based on their task performance, besides a compensation of ¥56 (about $8) per hour.

D. Procedures

Before starting the formal experiment, the participant sat in a height-adjustable office chair with a comfortable sitting position referring to daily preferences in the office. The requirements and rules of monetary incentives were explained to every participant by a text description before experiments. To minimize cumulative learning effects of the force control skill over time, every participant was permitted to practice at least three times freely and assessed whether the proficiency and performance had reached a plateau after the practice. Then, the participant was instructed to actively fit the HMD with eyes to ensure a clear view at an appropriate height. Every participant was required to maintain consistent arm posture in a session. The other non-tapping fingers on two hands were required to keep a comfortable and consistent gesture to minimize their effects upon reactions of the finger performing force control.

In the formal experiment, the EEG signal acquisition was conducted in parallel with the stimulus-response measurement in the discrete fingertip force control task. There was a rest interval of 2 min between consecutive sessions to reduce the fatigue. During the rest, each participant was asked to give feedback about their feelings and emotional states. If a certain participant reported fatigue or discomfort, an immediate rest of 3 $\sim$ 5 min would be added for this participant.

E. Data Analysis and Statistics

1) Behavioral Data: The variations in response time were taken as a measure of attentional state to examine within-subject moment-to-moment fluctuations in attentional stability. The RT variation in a task was taken as a common benchmark for the lapse-of-attention over time, thus, the trial-to-trial RT variability was analyzed using the variance time course (VTC) [11]. According to two referable methodologies studying behavioral and neural correlates of attentional states [2], [11], [27], an integrated method for trial-to-trial RT variability was used considering both the vigilance decrement and

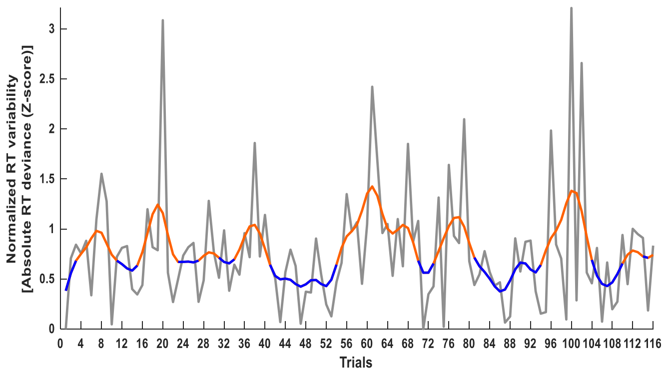

Fig. 3. Low-variability and high-variability epochs divided by smoothed VTC of a session. Blue line segments denoted the trials in the optimal attention state, and orange line segments denoted the trials in the suboptimal attention state.

the practice effect [24] over time in this study. Consequently, a dichotomous approach for the attentional states in a session was used to divide continuous performance into optimal and suboptimal states of task engagement [11], [24]. To weaken the impact of the initial state and task repetition on the RT variation, the VTC was computed from the 116 trials after removing the first, the two fastest, and two slowest RTs of each session. Using a moving window moved in increments of one trial, the normalized (Z-score) absolute deviation was calculated at each trial to map the trial-to-trial RT variation relative to the local dynamic inter-subject performance in a session. Specifically, a local RT variation of a trial was calculated by z-scoring over a certain number of adjacent trials. The mean and standard deviation of RT for the z-score was computed by all trials if the former trials were less than 20, and otherwise by the last 20 trials. Then, the VTC was smoothed using a Gaussian smoothing kernel of four trials full width at half maximum (FWHM).

After Gaussian smoothing, the median of smoothed VTC was used to classify each trial. Trials, whose smoothed VTCs were smaller than the median, were regarded as low-variability ones and the others were regarded as high-variability ones. As a result, all trials in a session were classified one by one. The segments composed of smaller VTC trials were marked with blue color, and the other segments composed of larger VTC trials were marked with orange color, as shown in Fig. 3. Therefore, 50% low-variability trials were classified to the low-variability epoch indexing the optimal state of sustained attention, while the other 50% trials were classified to the high-variability epoch indexing the suboptimal state of sustained attention. Thus, the low- and high-variability epochs were extracted from each session with a median split on the smoothed VTC. Then, the low- and high-variability epochs in the three sessions of each participant were spliced together. With these epochs of behavioral performance acted as hallmarks of attentional states, EEG signals would be mapped into the optimal or suboptimal state of sustained attention.

2) EEG Data Preprocessing and Feature Extraction: Original EEG signals were preprocessed offline using EEGLAB [40], an open-source toolbox running in the MATLAB environment. The EEG dataset of each participant was re-referenced offline to average activities over the scalp [41]. There were 60 EEG channels after excluding the EOG channels. Continuous EEG data were bandpass filtered between 0.5 $\sim$ 45 Hz (zero-phase FIR filtering with a hamming window function) [42]. EEG epochs were time-locked to the onsets of the visual cues (stimulus-locked) and haptic response (response-locked), respectively. The epochs were extracted using a window analysis time of 900 ms (300 ms pre-stimulus and 600 ms post-stimulus) and were further baseline corrected using the pre-stimulus interval. Epochs containing muscle activity, eye movements, or conspicuous artifacts due to other sources of noise were removed through visual inspection. Bad channels were interpolated with spherical spline interpolation. Subsequently, trials contaminated by eye-blinks or movements, and muscle activity were corrected using an independent component analysis (ICA) algorithm [38]. The criteria for removing and retaining independent components in artifact correction by ICA referred to the methods proposed in the literature [43]. After the ICA procedure, EEG data from the 12 participants were included in the following analysis because the other five participants were excluded from the data analysis due to extensive artifacts exceeding ±150 μV [41]. For each participant, EEG epochs belonging to the same attentional state were averaged together. Thus, the EEG data of each session were divided into two separate sets according to the two-class attentional states. Then, single-subject ERP data were averaged to obtain two grand-averaged ERP waveforms.

In previous studies [23], [31], [32], [38], typical ERP (N1, P1, N2, P2, and P3) peak deflections were identified on the grand-averaged waveforms. However, these existing ERP components could not be directly used in the current visuo-haptic interactive task before the validation. Because there might be significant variation in the temporal or spatial location of effects between experiments due to differences in design, stimulus characteristics, and novel conditions [44]. As a result, the ERP features of interest tended to vary from one experiment to the next. Given the possibility of task-specific biomarkers, a time point for each 50 ms on the two average ERP waveforms at each electrode was taken to search for possible ERP components in the current study, besides points with peak amplitude. At each point, an interval with a neighborhood interval of 20 ms was selected, as shown in Fig. 4. The candidate stimulus-based ERPs and their corresponding latencies in a region-of-interest (ROI) would be confirmed by comparing the average potential amplitudes between the two attentional states in each interval.

Both the data-driven ROI selection based on the scalp topographies and difference testing between two attentional states at each electrode were employed to define the ROI of this study. Using simulations of simple ERP experiments, Brooks et al. [44] demonstrated that data-driven ROI selection could indeed be more powerful than a priori hypotheses or independent information. The method proposed in Woltering's research on ADHD [45], using independent sample *t*-tests to test the differences at each electrode, was referable owing to a similar theme. Given the different designs of the current experiment, the two-tailed paired *t*-tests were adopted to

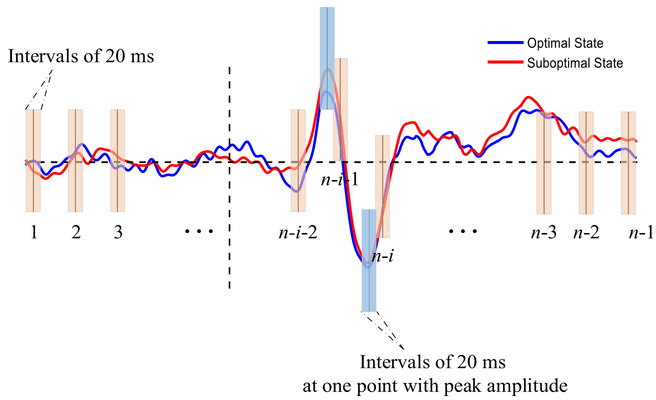

Fig. 4. Intervals of 20 ms for finding possible ERP components.

examine the 60 electrodes one-by-one with a direct FDR correction [46]. For a participant, each of the selected electrodes in an ROI had to meet two requirements: a greater grand-averaged amplitude on the scalp topography and a significant difference between the two attentional states in an interval. Wherein, we made the first *t*-test at each electrode, considering the average potential in an interval as variable and the attentional state as grouping variable. Significant effects were further investigated using the one-way repeated measure ANOVA for the average potentials in each ROI, and p value was retained as significant difference when it was lower than 0.00083 after applying Bonferroni corrections for multiple comparisons [5], [45]. Accordingly, the ROIs and the candidate stimulus-elicited ERPs were roughly extracted. Then, the average waveforms of the candidate stimulus-elicited ERPs were obtained by averaging over all electrodes in each ROI for each participant. Based on the average waveforms, each of the candidate stimulus-elicited ERPs would be further verified whether its significant difference between the two attentional states did survive from Bonferroni correction. Finally, a candidate stimulus-elicited ERP and its latency would be one of the expected ERP characteristics after surviving the correction.

According to the behavioral task of stimulus-response in this experiment. Every trial contained a complete visual cue perception and a finger force control response. Thus, the top-down cognitive performance of sustained attention was more likely to be reflected in the overall difference of each test, compared with the bottom-up time-related potentials evoked by visual cues or finger force. The EEG epoch for every trial was extracted from the continuous EEG data at the onsets of the visual cues to investigate the power spectra of EEG oscillations. A Fast Fourier Transform (FFT) was run with a Hanning window to obtain the power spectrum (PS) estimation for each trial at each electrode. The window length was the signal length of a trial because the duration of each trial was different, which depended on the speed of the subjects' continuous response. Then, EEG power spectra were log-transformed after the data were extracted into five different frequency bands: delta rhythm ($\boldsymbol{\delta}$, 1.0 $\sim$ 4.0 Hz), theta rhythm ($\boldsymbol{\theta}$, 4.0 $\sim$ 8.0 Hz), alpha rhythm ($\boldsymbol{\alpha}$, 8.0 $\sim$ 13.0 Hz), beta rhythm ($\boldsymbol{\beta}$, 13.0 $\sim$ 30.0 Hz) and gamma rhythm ($\boldsymbol{\gamma}$, 30.0 $\sim$ 45.0 Hz), respectively [47], [48]. The spectral powers of all trials were averaged to obtain the mean band power for each frequency band at each electrode between the optimal and suboptimal attentional states. Therefore, the grand-averaged powers of $\boldsymbol{\delta}$, $\boldsymbol{\theta}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, and $\boldsymbol{\gamma}$ bands could be obtained separately by averaging the mean band powers of all participants. After determining the ROI of each band using a similar method for the ROI selection of stimulus-based ERPs, the mean band powers of all electrodes in the ROI were further averaged for each participant. In line with the ERPs analyses, following statistical analyses of band powers among all participants were performed in each of five frequency bands.

IV. Results

A. Cumulative Learning Effect on Behavioral Performance

We examined whether the reaction efficiency and the RT coefficient of variation differed across the three sessions to confirm if there was a cumulative learning effect on behavioral performance in the current force control task. A learning effect in the response efficiency was found during the discrete multi-finger force control training in a previous study [17]. First of all, a Shapiro-Wilks test was run to check the data normality of the reaction efficiency and the RT coefficient of variation. Then, a one-way repeated measure ANOVA showed that the reaction efficiencies did not significantly differ across the three sessions, $F(1.327, 14.6) = 0.858$, $p = 0.401$, $\boldsymbol{\eta}^2 = 0.072$. The partial $\boldsymbol{\eta}^2$ was reported as an estimate of effect size for ANOVAs. The fractional degree of freedom was due to the Greenhouse-Geisser correction when Mauchly's Test of Sphericity showed that the assumption of sphericity had been violated. Furthermore, the one-way repeated measure ANOVA showed that the differences in RT coefficient of variation were not significant between the three sessions, $F(2, 22) = 0.1$, $p = 0.905$, $\boldsymbol{\eta}^2 = 0.009$. Consequently, even though each participant repeatedly performed three sessions in the current experiment, no cumulative learning effect of gradual improvement was shown in the reaction efficiencies. The experimental design of this study effectively eliminated the cumulative learning effect throughout the measurements.

B. Visual Stimulus-Elicited ERPs

Several candidate EEG characteristics for indexing two states of sustained attention were summarized in Table I with statistical analyses using the one-way repeated measure ANOVA. The Shapiro-Wilks test showed that samples of all brain responses of ERPs and PS complied with the normal distribution, except for the delta band ($p < 0.05$). Therefore, a Wilcoxon signed ranks test was run to confirm if there were differences in the average powers of delta band between the optimal and suboptimal states of sustained attention.

In the optimal and suboptimal states of sustained attention, ROI-based analyses for the visual stimulus-locked ERPs were shown in Fig. 5. The visual-elicited ERP amplitudes were measured at frontal electrodes (F1, F2, F3, F4) and parieto-occipital electrodes (PO3, PO5, PO7, O1, PO4, POz, Oz, O2) of each participant. Two visual-locked grand-averaged

TABLE I
SUMMARY STATISTICS FOR ELECTROENCEPHALOGRAPHIC CHARACTERISTICS

ERP/PS	Brain responses	Mean		Std. Dev.		One-way repeated measure ANOVA		
		Optimal	Suboptimal	Optimal	Suboptimal	$F(1, 11)$	p	Partial η^2
ERPs (μV)	Stimulus-elicited N1	-1.1422	-1.4083	1.0246	1.0468	10.026	0.009	0.477
	Stimulus-elicited P1	1.8286	2.0997	1.315	1.3594	11.508	0.006	0.511
	Response-elicited N_{ep}	-1.0011	-1.3047	1.2396	1.2495	39.554	0.00006	0.782
	Response-elicited P_{ep}	1.0241	1.2699	1.0352	1.0673	12.875	0.0043	0.539
PS (μV²/Hz)	Delta rhythms	70.4878	71.3551	7.8121	7.5142	Z = -2.197	0.028	---
	Theta rhythms	54.114	54.6186	3.0956	3.1252	16.681	0.0018	0.603
	Alpha rhythms	42.4351	43.018	2.4445	2.5642	24.943	0.0004	0.694
	Beta rhythms	49.0172	49.5122	6.3089	6.2574	23.363	0.0005	0.680
	Gamma rhythms	43.7376	44.2273	6.7769	6.7394	27.473	0.0003	0.714

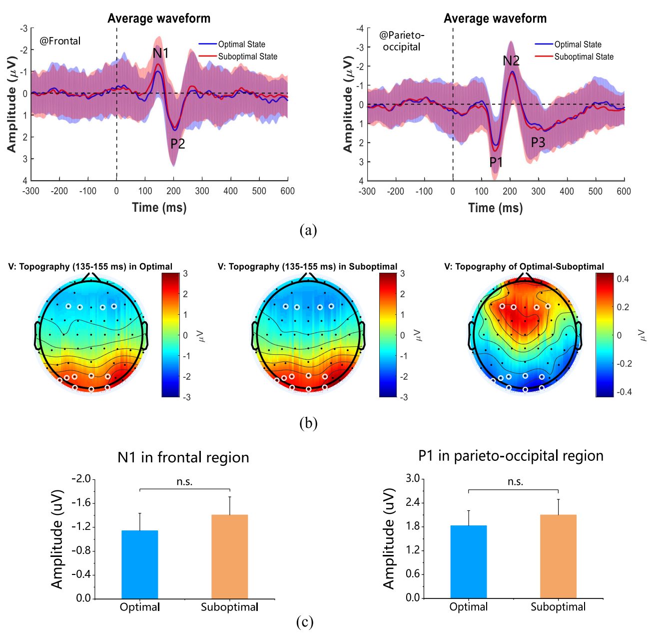

Fig. 5. Visual stimulus-locked ERPs. (a). The grand-averaged stimulus-elicited ERPs waveforms. Difference in deflections within 135 ~ 155 ms after visual cues onset between optimal state and suboptimal state. (b). The scalp topographies of the peak deflections. Electrodes with significant effect were marked using enlarged white dots at a 0.05 level. (c). The statistical results for the means and standard deviations of the visual N1 and P1 components between optimal and suboptimal states. Data were expressed as mean ± SEM. **: $p < 0.00083$; n.s.: $p > 0.00083$.

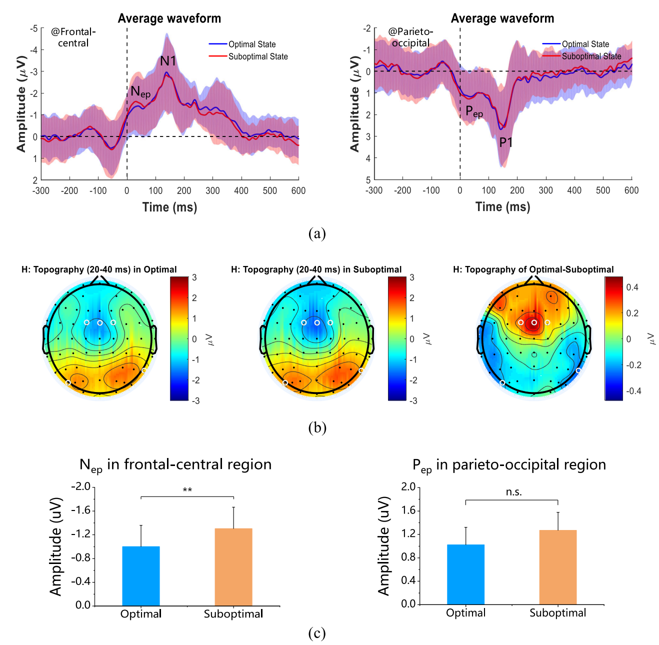

Fig. 6. Haptic response-locked ERPs. (a). The grand-averaged response-elicited ERPs waveforms. Difference in deflections within 20 ~ 40 ms after haptic response onset between optimal and suboptimal states. (b). The scalp topographies of the peak deflections. Electrodes with significant effect were marked using enlarged white dots at a 0.05 level. (c). The statistical results for the means and standard deviations of the haptic N_{ep} and P_{ep} components between optimal and suboptimal states. Data were expressed as mean ± SEM. **: $p < 0.00083$; n.s.: $p > 0.00083$.

waveforms and error bands in the two attentional states were analyzed, as shown in Fig. 5 (a). There were two obvious candidate visual-elicited ERP components N1 and P1 in a latency interval of 135 ~ 155 ms. The N1 and the P1 showed greater grand-averaged amplitudes in the suboptimal state of sustained attention, compared with the optimal state of sustained attention. These differences (optimal minus suboptimal) of the visual-elicited N1 and P1 between two states of sustained attention were presented with the scalp topographies, as shown in Fig. 5 (b). The maximal differences in the grand-averaged ERP amplitudes were distributed over frontal regions for N1 and parieto-occipital regions for P1. Furthermore, Fig. 5 (c) showed the mean potentials and standard errors of the N1 in the frontal electrodes as well as the P1 in the parieto-occipital electrodes. However, as listed in Table I, the differences of visual stimulus-elicited N1 and P1 did not survive from Bonferroni correction for multiple comparisons (Bonferroni-adjusted level of significance: $p < 0.00083$). As a result, no visual-elicited ERPs were found to be significantly different between the suboptimal and optimal states of sustained attention.

C. Haptic Response-Elicited ERPs

In line with the method for visual stimulus-elicited ERPs, similar analyses for the haptic response-elicited ERPs were also conducted between the optimal and suboptimal states of sustained attention, as shown in Fig. 6. The haptic response-elicited ERPs at frontal-central electrodes (FCz, FC1, FC2) and parieto-occipital electrodes (P8, PO7) were measured. In Fig. 6

(a), the response-locked grand-averaged ERP waveforms and error bands were shown in the optimal and suboptimal states of sustained attention. In a latency interval of 20 $\sim$ 40 ms after the haptic reaction onset, two early local deflections of haptic response-elicited ERP components were found in the grand-averaged waveforms. Herein, the early negative and positive peaks among the two local deflections were named N_{ep} and P_{ep}, respectively. Accordingly, a more negative grand-averaged N_{ep} could be observed by the haptic response in the suboptimal attentional state, compared with the optimal attentional state. While the grand-averaged P_{ep} showed to be more positive in the suboptimal attentional state than in the optimal attentional state. These differences (optimal minus suboptimal) of the haptic-elicited N_{ep} and P_{ep} were displayed with the scalp topographies in Fig. 6 (b). These differential ERP amplitudes were maximal over frontal-central regions for N_{ep} and parieto-occipital regions for P_{ep}. Moreover, the mean potentials and standard errors were presented for the N_{ep} at the frontal-central electrodes and the P_{ep} at the parieto-occipital electrodes, as shown in Fig. 6 (c). It was further verified that the haptic-elicited N_{ep} indeed differed significantly ($p < 0.00083$) between the suboptimal and optimal states of sustained attention after Bonferroni correction. While the differences of haptic-elicited P_{ep} were not significant. Additionally, although there was a small amount of residual amplitude fluctuation in the baseline of -300 $\sim$ 0 ms in the haptic response-locked ERP waveforms no significant difference of residual amplitude within the baseline was observed between the optimal and suboptimal states of sustained attention.

D. Powers of Different Frequency Bands

The power spectrum estimation was conducted for each of five frequency bands between the suboptimal and optimal states of sustained attention. As shown in Fig. 7, the differences (optimal minus suboptimal) of the band powers between the suboptimal and optimal states of sustained attention were presented by the scalp topographies of five frequency bands. The grand-averaged powers in the delta band were measured at a prefrontal electrode (AF4). The grand-averaged powers in the theta band were measured at frontal and parietal-central electrodes (F2, F3, FCz, FC2, FC3, Cz, C1, C2, CP1, and CP2). The grand-averaged powers in the alpha band were measured at frontal-central, temporal, and parietal-central electrodes (FC1, FC3, C1, C3, C6, T8, and CP6). The grand-averaged powers in the beta band were measured at prefrontal and temporal electrodes (Fp1, Fp2, F4, F6, FC6, and FT8). The grand-averaged powers in the gamma band were measured at frontal and temporal electrodes (Fp2, AF3, AF7, FC6, and FT8). Since the Shapiro-Wilks test showed that the delta band powers violated the normality assumption, the Wilcoxon signed ranks test was adopted and showed that the delta powers differed in two states of sustained attention (z = -2.197, p = 0.028 < 0.05). However, it was abnormal that the topography of delta power was constrained within a single electrode, as shown in Fig. 7. Additionally, the statistic differences in delta and theta band powers did not survive from

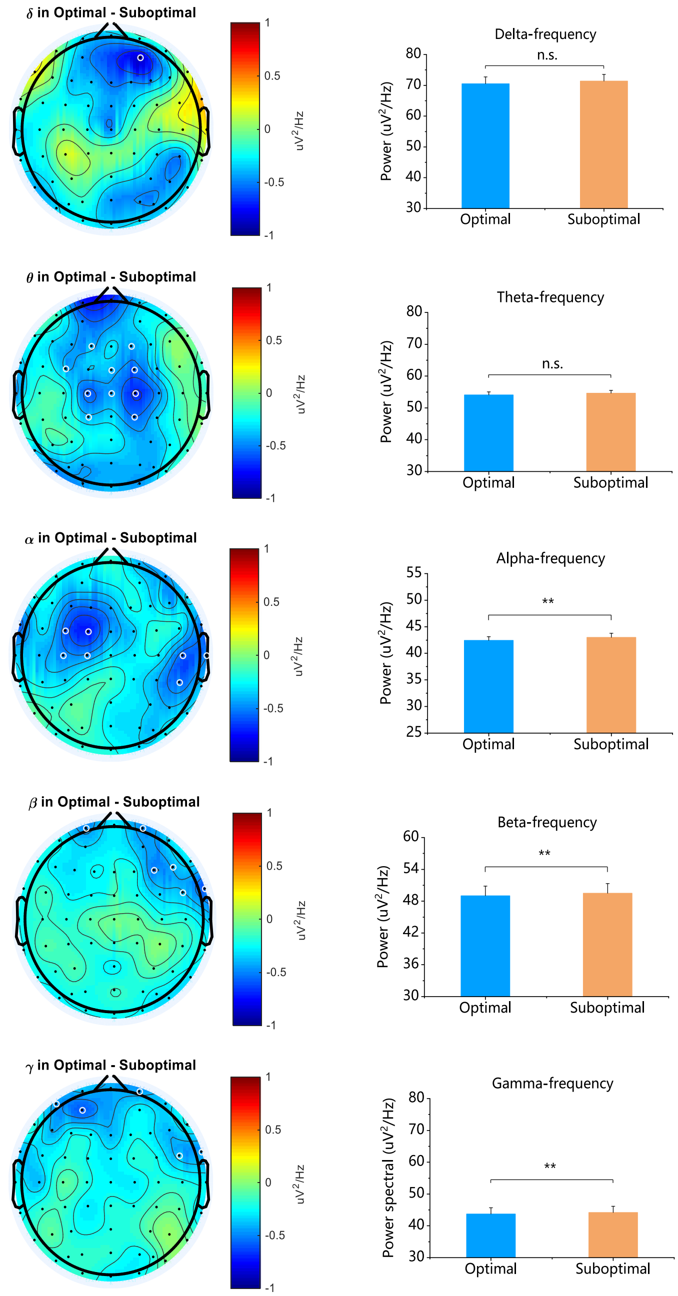

Fig. 7. Scalp topographies of mean powers differences (optimal minus suboptimal activity) between optimal and suboptimal states for five frequency bands. The mean powers were computed over segmented epochs based on the onsets of visual cues. Electrodes with significant effect were marked using enlarged white dots at a 0.05 level. Data were expressed as mean $\pm$ SEM. **: $p < 0.00083$; n.s.: $p > 0.00083$.

Bonferroni correction ($p > 0.00083$), although p values of difference analysis for these two band powers were less than 0.05, as shown in Table I. the smallest p-value and the largest effect size seemingly supported the significant differences of gamma-band between the two attentional states. Whereas, it was noted that all electrodes in the ROI of the gamma band were almost distributed on the edge of the prefrontal and temporal regions. Although the difference in the beta band power between the two states of sustained attention also survived from Bonferroni correction, the p-value was a little larger and the effect size value was a little smaller than those of the alpha band. In contrast, a significant decrease ($p < 0.00083$) of the alpha band power was confirmed with a relatively large effect size η^2 over the frontal-central, right temporal, and parietal-central regions in the optimal state of sustained attention.

V. Discussion

Neural markers of sustained attention were prerequisites to further study the neurocognitive mechanisms of cognitive control involved in the process of training [49]. After an unprecedented surge in identifying the therapeutic efficacies, scientists were increasingly interested in the neurocognitive mechanisms involved in training processes [24]. The dynamic effects of the training task and the optimal training dosage to generate the significant efficacy would remain unknown for game designers if how well participants were attentive from moment to moment was not detected [17], [31]. In the proposed visuo-haptic finger force control task, sustained attention was confirmed to be related to the early haptic-elicited N_{ep} in the frontal-central region and the alpha-band powers in the frontal-central, right temporal, and parietal-central regions. These findings would be conducive to understanding the neurophysiological mechanism of sustained attention using discrete finger force control and developing a closed-loop neurofeedback attention training system by monitoring states of sustained attention in the training process [10], [24].

A technical platform was also proposed to integrate the 64-channel EEG acquisition and the HMD for VR. Haptic systems and devices have widespread applications such as medical and cognitive training, assistive, and rehabilitative devices for individuals who suffer from physical or neurological impediments [13]. The proposed platform has the potential to be a useful tool for different task domains and/or clinical applications [50], [51], for instance, clinical assessments of finger motor dysfunction for Parkinson's disease [52]. The proposed method would be also applicable to real multi-finger interaction when using the index and middle fingers of both hands. These four fingers were demonstrated to be not significantly different in the finger force control ability [53]. Moreover, Wang et al. [54] used the same brand of 32-channel EEG equipment to decode single-hand and both-hand movement directions from noninvasive neural signals.

The nonsignificant difference in the visual stimulus-elicited components N1 and P1 might be accounted for by an interpretation that these two ERPs were not quite sensitive to the sustained attentional states. Hasler et al. [32] did not observed significant effect of cue- or target-related ERPs on P1 and N1 amplitudes, supporting similar initial sensory-level processing at the early stages of visuocortical analysis. Since P1 and N1 were early ERP components indexing processing during the sensory input stage, their reduction was taken as evidence supporting an inhibitory effect of mind-wandering on external perception [55]. Whereas, sustained attention represented an essential attentional function that determined the efficacy of the higher aspects of attention and cognitive capacity in general [10], [34]. Sustained attention performance associated with activation of the basal forebrain corticopetal cholinergic system was conceptualized as a component of the top-down processes initiated by activation of the anterior attention system [34]. These findings suggested that the effect of sustained attention on the ERPs elicited by the external visual cues would be apparent only if the visuocortical activation could be transmitted to the forebrain corticopetal cortex. In the proposed visuo-haptic task, visual cues might be so easily noticed that it was not necessary for the involvement of higher-order cognitive processes [39].

The emergence of an early local deflection might not be surprising for the response-locked analysis, especially in a fast-paced stimulus-response task. In the study of Olfers et al. [56], both the stimulus-locked and response-locked ERP analyses were used to study the transfer effect of game-based cognitive training. An early peak with a latency of $23 \sim 47$ ms was also illustrated in the response-locked ERP waveforms. The attenuation of the early ERP deflection N_{ep} elicited by the haptic response might be a late visual-elicited component in the optimal state of sustained attention. Although this reasoning could not be verified in the current study, there were three supporting reasons. First, the responses to visual cues in the current experimental task were required immediately. Some RTs were so short that it might lead to overlapping in ERP latencies of visual cues and haptic responses. Second, as shown in Fig. 6, a later peak N1 following N_{ep} emerged in the haptic-elicited ERP waveform. This emergence indicated that N_{ep} might be one of the late ERPs elicited by visual cues, and the later haptic-elicited N1 might be the actual ERP elicited by the reaction of finger force control. The early ERP components were usually related to basic sensory stimulus processing (e.g., N1 and P1), while the late components reflected perceptual and cognitive processes, including encoding, classification, task control, selection, and motor response preparation [32]. Third, if the haptic-elicited N_{ep} was a late visual-elicited component, its attenuation could be attributed to the attention resource allocation in the fine finger force control process, reducing the late investment in visual cues processing [57], [58]. Werkhoven et al. [59] found that vision was also more easily suppressed by top-down selective attention in a study on the effect of attention on multisensory integration.

The proposed visuo-haptic fingertip force control task is a fast-paced customized game for attention training rather than a psychological lab paradigm with a long interstimulus interval (ISI) for typical ERP analysis. Bavelier et al. [29] argued that users immersed in fast-paced events in the digital fantasy world could gain significant cognitive advantages. To develop new therapeutic games, researchers began to take the essence of both commercial video games and traditional cognitive tests that were unsuitable for real-world attention training. These new games bore little resemblance to drab psychological tests, making them quite suitable for home rehabilitation [17], [29]. Accordingly, a practical design that the one-by-one trials appeared immediately was adopted in the proposed task. One of the further studies could be conducted by lengthening the inter-stimuli interval (ISI) of the current visual-haptic task. Consequently, we could not only investigate how a different baseline would impact the ERP during the anticipatory period but also explore the effect of visual or haptic in multisensory integration [60], [61]. The following studies would be conducive to revealing the attention network to process haptic interactive information in the somatosensory area [13]. This interesting issue was what many researchers in the neurohaptics field are devoting to [62]–[64].

The current study revealed suppression of alpha-band power in electrodes that covered frontal-central, right temporal, and parietal regions under the optimal attentional state, compared to the suboptimal state of sustained attention. This finding was consistent with previous revelations suggesting a role of the right fronto-parietal network in sustained attention, as well as the role of alpha in these regions in sustained attention control [37], [65]. Recently, converging electrophysiological evidence supporting that alpha oscillations played an important and active role in cognitive processing [66]. Sadaghiani et al. [65] suggested that three large-scale brain networks involved in different facets of top-down cognitive control differentially modulate α-oscillations, ranging from power within and synchrony between brain regions. The inhibitory role of alpha-band activity was also found in sustained attention during a multi-object selective attention task to extract object-specific neuronal responses [67]. These findings further corroborated that alpha power could reflect the alternating states of sustained attention. Whereas, the gamma band was not suitable to act as an expected feature to characterize the states of cognitive attention. As shown in Fig. 7, the abnormal scalp topographies of the delta and gamma-band powers were more likely to be associated with electrode artifacts and residual muscle artifacts, respectively. An abnormal topography constrained within a single electrode could be appeared due to electrode artifacts [43]. The frequency of artifact-relevant components was in a higher frequency band (e.g., >30 Hz), while the frequency content of neural signals was in a lower frequency band (e.g., $5 \sim 20$ Hz) [43]. Principal sites of generating muscle artifacts were located at frontalis and temporalis muscles [68].

The current work could be improved with two follow-up studies. All trials in the presented experimental task were set to the same difficulty level to eliminate the effect of task difficulty on the RT variation. Future studies should quantify the relationship between sustained attention modulated oscillatory neural activities of the alpha band and task difficulty to develop visual-haptic tasks with adaptive difficulty adjustment for long-term attention training based on current findings. Furthermore, a longitudinal follow-up study could further investigate the spatial specificity and traceability of the right fronto-parietal region regulating the power growth of the alpha band in EEG source analysis [10]. We could enhance understandings of the brain networks and alpha oscillations for structural and functional foundations of cognitive control [65]. Besides, it remained unknown whether the proposed EEG markers of optimal attention were generalizable for other sustained attention processes. One of the horizontal studies would be to apply the same method in the proposed VR task but using key-pressing modality without fine multi-finger force control. If the same EEG markers indexing the two states of sustained attention can be found in different response modalities, the impact of current study will be broader. If different EEG markers can be revealed, then we will learn something important about how the haptic environment influenced these markers in optimal sustained attention.

VI. Conclusion

Understanding psychophysics, biomechanics, and neurological effects in haptic interaction are instructive to develop an intelligent and effective human-computer system for rehabilitative applications. The reported study in this paper aimed to characterize the neuro-cognitive states of sustained attention in an immersive visuo-haptic task using discrete fingertip force control. Sustained attention in the visuo-haptic task was divided by variation of RT into two levels: the optimal state with low-variability RTs and the suboptimal state with high-variability RTs. Consequently, we identified two EEG features: a decreased frontal-central ERP component N_{ep} elicited by fingertip pressing force and oscillatory alpha-band suppression over the frontal-central, right temporal, and parietal-central regions in the optimal state of sustained attention. These findings enriched the understanding of the neurocognitive mechanism of sustained attention during multi-finger haptic interaction of force control as well as would be able to serve as candidate biomarkers for monitoring the state of sustained attention, laying an essential foundation to develop a closed-loop neurofeedback system of attention training using visuo-haptic interaction in an immersive environment.

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