

# Neurofeedback training of control network improves SSVEP-based BCI performance in children

Sun Jingnan (✉ [sjn17@mails.tsinghua.edu.cn](mailto:sjn17@mails.tsinghua.edu.cn))

Tsinghua University

Jing He

Tsinghua University

Xiaorong Gao

Tsinghua University

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## Research

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# Abstract

**Background:** In the past 20 years, neural engineering has made unprecedented progress in the interpretation of brain information (e.g., brain-computer interfaces) and neuromodulation (e.g., electromagnetic stimulation and neurofeedback). However, the study of improving the performance of the brain-computer interface (BCI) using the neuromodulation method rarely exists. The present study designs a neurofeedback training method to improve the performance of steady-state visual evoked potential (SSVEP) BCI and further explores its underlying mechanisms.

**Methods:** As parietal lobe is the sole hub of information transmission, up-regulating alpha-band power of the parietal lobe by neurofeedback training was present as a new neural modulating method to improve SSVEP-based BCI in this study.

**Results:** After this neurofeedback training (NFT), the signal-to-noise ratio (SNR), accuracy, and information transfer rate (ITR) of SSVEP-based BCI were increased by 5.8%, 4.7%, and 15.6% respectively. However, no improvement has been observed in the control group in which the subjects do not participate in NFT. What's more, a general reinforcement of the information flow from the parietal lobe to the occipital lobe was also observed. Evidence from the network analysis and attention test further indicate that NFT improves attention via developing the control ability of the parietal lobe and then enhances the above SSVEP indicators.

**Conclusion:** Up-regulating parietal alpha-amplitude using neurofeedback training significantly improves the SSVEP-based BCI performance through modulating the control network. The study validates an effective neuromodulation method, and possibly also contributes to explaining the function of the parietal lobe in the control network.

## 1. Introduction

The study of cortical oscillations observed in the electroencephalogram (EEG) that have made significant progress recently. The effects and influences of various rhythms on people have gradually been researched since the neural oscillations were first discovered by Hans Berger (Berger, 1929). However, the physiological mechanisms by which cortical oscillations affect human behavior are still not fully understood. Some studies indicated that the roles of neural oscillations include feature binding, information transfer mechanisms, and the generation of rhythmic motion output (Klimesch, 1999; Buzsaki, 2004; Canolty et al., 2006; Buzsaki et al., 2013; Iaccarino, 2016). In recent decades, a few breakthroughs have been made by electroencephalography and neuroimaging in this field. It has been found that neural oscillations play an essential role in the processing of neural information. However, there is little experimental evidence to reveal the function of neural oscillation so far. And it is unlikely to make an accurate explanation for the role of neural oscillation. Further insights into neural oscillations and their relationship to cognitive processes are key research fields of neuroscience. Furthermore, the

specific characteristics of the oscillations could be regulated and controlled to achieve functional changes purposefully.

Alpha-band oscillations are the dominant oscillations in the human brain. Although the physiological basis of alpha is still unclear, the origin of it is thought to be related to the thalamo-cortical structures (Lopes da Silva et al., 1973; Nunez et al., 2001; Nicoletti and Faselow, 2002; Lőrincz, 2009; Hughes, 2011; Schmid, 2012; Howells et al., 2018). More and more recent research on alpha-band function has pointed out that alpha-band acts as a significant inhibitory function in information processing of the brain. Previous work pointed out the idea that information is routed by functionally blocking off the task-irrelevant pathways (gating by inhibition). Importantly, this inhibition is reflected by oscillatory activity in the alpha band. And the activation and inhibition of different regions (task-state) are present in the form of attention (Jensen and Mazaheri, 2010). Moreover, the evidence is presented that alpha-band oscillations reflect cognitive and memory performance and state. Alpha-band oscillations enable voluntary orientation of attention and controlled knowledge access since they are closely linked to the fundamental function (suppression and selection) of attention (Klimesch, 2012). The traditional argument about the role of alpha band activity in attention is that alpha oscillations desynchronize in response to anticipatory attention and in the absence of stimulus. This type of event-related desynchronization (ERD) is termed as “prestimulus, anticipatory ERD”. Large prestimulus ERD is relevant to high detection performance (Ergenoglu et al., 2004; Hanslmayr et al., 2005), which reflects the maintenance of target information in an attentional buffer. Furthermore, an increase in amplitude of event-related synchronization (ERS) reflects inhibition. While a decrease in amplitude of event-related desynchronization (ERS) reflects release from inhibition. For instance, in tasks that vary stimulation side (e.g., stimulation of the right vs left visual hemifield), stimulus modality, or stimulus processing domain (e.g., related to the ventral vs dorsal processing stream). Findings display that when attention is focused on the auditory section of a compound auditory-visual stimulus, alpha oscillation is larger over visual cortices (Foxe et al., 1998). When a task engages the ventral stream, alpha power is larger over parietal regions (Jokisch, 2007). What's more, the ability of the human response to visual stimuli based on their spatial locations which requires the parietal cortex to attend (Corbetta, 2000) for the attention of visual tasks. One theory maintains that the parietal cortex controls the autonomous orienting of attention toward a location of interest (Mesulam, 1981; Heilman et al., 1985; Halligan and Marshall, 1994). Another emphasizes its role in reorienting attention toward visual targets appearing at unattended locations (Posner et al., 1984; Morrow and Ratcliff, 1988; Di Pellegrino, 1995; Friedrich et al., 1998). All research above suggested that the parietal lobe was closely related to the attention of visual stimuli and played a crucial role in controlling and monitoring.

Neurofeedback training as an operant conditioning method that helps subjects to control or change their brain activity (Schafer and Moore, 2011). The training enables the modulation of neural oscillations voluntarily by real-time feedback of the brain's electrical parameters. Neurofeedback training is regarded as a safer and more stable method that could control or change neural oscillations than electromagnetic stimulation. Since then it has applied to several application scenarios (Zoefel et al., 2011), such as curing attention-deficit hyperactivity disorder (Arns et al., 2009; Sonuga-Barke et al., 2012), epilepsy (Zhao et al.,

2009), Huntington's disease (Papoutsis et al., 2017), improving cognitive performance (Vernon et al., 2003; Hanslmayr et al., 2005) and enhancing self-regulation of emotional and behavioral control (Mayeli et al., 2019).

At present, NFT is also applied to improve the performance of various types of BCI. As a form of classical BCI paradigm, SSVEP is also an essential part of the BCI with many applications. SSVEP can be understood as a phase-locked human brain that spontaneously responds to stimulation, and uses signal-to-noise ratio (SNR) to evaluate the signal quality most commonly. Despite decades of research, the performance of SSVEP-based BCI still highly relies on subject and algorithms (Neuper and Pfurtscheller, 2010). SSVEP signal and performance could be influenced by NFT so that Mayra pointed out that subjects can not accept any form of NFT before data collecting in the recent study about SSVEP-based BCI algorithm (Mayra et al. 2018). The study of Ordikhani-Seyedlar suggested that the power of the SSVEP signal was regulated by the attention of various degrees whatever covert or overt attention (Ordikhani-Seyedlar, 2014). Also, Collura designed experiments to demonstrate the relationship between periodic SSVEP and short-term attention (Collura and Thomas, 2002). Moreover, their works pointed out that the stimulation which combining attention and SSVEP was itself a kind of neurofeedback and was expected to be a way to train attention deficits. As for the application of neurofeedback in SSVEP field, Bruno's research claims to improve the visual and auditory cognitive by binaural audio and SSVEP neurofeedback (Bruno et al., 2017).

When it comes to the relationship between attention and SSVEP, Morgan provided more direct evidence. That is, he had asked the subjects to gaze at the center of the screen and set flicker stimulation blocks of different frequencies on both the left and right sides (Morgan et al., 1996). This attention-biased experiment found that the EEG of the subject experienced the frequency of stimulation in the lateral direction of the attention, thus demonstrating the correlation between attention and SSVEP.

Based on the above descriptions, since alpha oscillation has inhibitory function physiologically and SSVEP-based BCI performance seems like high attention required task, we came up with our hypothesis that improving the alpha amplitude of the parietal lobe could increase attention and the SNR of the SSVEP signal to enhance the SSVEP performance.

## **2. Materials And Methods**

### **2.1 Design**

The flow chart (Fig. 1) showed the experiment design detailedly. For each subject of the NFT group, the experiment consisted of twenty-four training sessions within two months. Participants were supposed to have three sessions (every session lasted for an hour) a week. In each session, subjects were asked to play an EEG feedback game. They were free to select three days to receive training in a week, with at least one day between two sessions. In order to ensure the interests of the subjects, the feedback interface was

presented to the subjects in the gamification approach with a controllable process. The SSVEP typing test was arranged to compare performance about ten days before and after the two months of training.

## 2.2 Participants

A total of forty-seven subjects (they were randomly assigned to two groups), twenty-five in the NFT group and twenty-two in the control group, took part in the experiment. Subjects with normal vision or corrected vision and no epilepsy or other diseases were selected. The written consent form was received from all of the participants' guardians. Moreover, the project is also reviewed by the Ethics Committee of the Tsinghua University School of Medicine. The final sample consisted of 24 subjects in the NFT group (six females and eighteen males,  $9.42 \pm 2.58$  years) and 22 subjects in the control group (eight females and fourteen males,  $9.86 \pm 3.14$  years). As van Praag's experiment suggested, aging causes changes in the hippocampus that may lead to cognition and neural plasticity decline in older adults (van Praag, 2005). Therefore, this research chose children to participate in neurofeedback training out of consideration for the young brains are more neuroplastic.

## 2.3 EEG Recordings

EEG data were recorded from 64 electrodes positioned according to the international 10–20 system (AF3/4, AF7/8, Fp1/2, FPz, Fz, F1/2, F3/4, F5/6, F7/8, FC1/2, FC3/4, FC5/6, FCz, FT7/8, Cz, C1/2, C3/4, C5/6, T3/4, T7/8, TP7/8, CP1/2, CP3/4, CP5/6, Pz, P3/4, P5/6, P7/8, PO3/4, PO5/6, PO7/8, POz, Oz, O1/2, HEOL, HEOR, ECG, VEOL, VEOU) and referenced to CPz. A portable wireless EEG amplifier (NeuSen.W64, Neuracle, China) was used for data recording at a sampling rate of 1000 Hz. Electrode impedances were kept below 10 kOhm for all electrodes throughout the experiment. The experiment was carried out in a natural office environment without any electrical shielding.

## 2.4 alpha-band power ratio

In this study, neurofeedback training was performed to increase the alpha-band amplitude. The alpha-band power was calculated in order to examine the training outcome. Since the absolute value of the alpha-band amplitude is affected by the current state of the subject and the environment, they are not comparable between different trials. In the aim to contrast the results of NFT parallelly, we calculate the ratio of the power which the alpha-band to the 0.8 Hz-20 Hz band to characterize whether the alpha amplitude is improved. In the following formula,  $X_1$  and  $X_2$ , denoting the power of the alpha band and full band. In the formula,  $X$  denotes the EEG signal and  $f$  denotes the frequency.

$$\begin{aligned}
X(f) &= \text{fft}(X) \\
X_1 &= \sum_8^{12} |X(f)|^2 \\
X_2 &= \sum_{0.8}^{20} |X(f)|^2 \\
P_{\alpha} &= \overline{X_1} / \overline{X_2}
\end{aligned} \tag{1}$$

The resting-state data was obtained by two-minute open-eye and two-minute closed-eye experiments. The closed-eye data totaled 120,000 sampling points with a sampling rate of 1000, and the frequency domain resolution was 1/12 Hz.

## 2.5 SSVEP stimulation

The processing system consists of a stimulation device, an EEG acquisition device, and a processing computer. The stimulation device is ASUS MG279Q 27-inch display with 2560\*1440 resolution and 143 Hz refresh rate. The processing device is an Intel i9-9900K@3.6 GHz CPU and DDR4 32 GB memory. Stimulation and processing programs were developed under Matlab 2015a and Psychophysics Toolbox Version 3.

During the experiment, the stimulation was presented in the form of a multi-target flicker. A start trigger and an end trigger signal were sent to the EEG collector at the beginning and end of each trial. The processing device receives the EEG data from the EEG amplifier in real-time and feeds the judgment results back to the stimulation device after the identification is completed.

As the Fig. 2 and Fig. 3 shown, in the SSVEP test, a 40-target SSVEP speller based on frequency phase modulation coding (frequency range: 8-15.8 Hz, frequency interval: 0.2 Hz) was used (Chen et al., 2015). A total of 40 stimulus target blocks were set on the screen, which respectively represents A-Z with a total of 26 letters, 0–9 total ten digits, spaces, commas, periods, and backspace keys. In the experiment, each stimulus target was constructed by sampling the sinusoidal method (Chen et al., 2014; Manyakov et al., 2013).

In the entire SSVEP task, in order to guarantee the actual state of subjects and the validity of the data, the staff required each subject to complete six blocks (40 trials each block). Participants can choose to rest between blocks to perform their best. Thus, the entire test takes about 40 minutes.

## 2.6 SSVEP performance calculation

The entire online test (feedback results in real-time) is divided into six blocks. The four blocks prior use a 3–4 second dynamic window and are classified applying the filter bank canonical correlation analysis (FBCCA) algorithm (Chen et al., 2015). The last two blocks use a 1–2 second dynamic window and

applying the task-related component analysis (TRCA) algorithm for classification (Nakanishi et al., 2017), where the training data for TRCA was the four blocks prior. Moreover, for each target, six trials take into consideration.

The average SNR of nine leads in the occipital lobe (PO3/4, PO5/6 PO7/8, Oz, O1/2) and the information transfer rate (ITR) were examined to estimate the SSVEP performance of the subjects. In the formulas below, N is total target numbers, A means accuracy, T represents the time required to identify.

For the SNR calculation, flexible band definitions around signals and noise could be made as needed in the engineering project. In this study, SNR was used as an indicator of SSVEP performance to minimize the effect of the background EEG activity across subjects. Therefore, the power of the signal is specified that the power of a narrow frequency interval centered on the stimulus frequency ( $f \pm 0.2$ ). At the same time, the power of a broader scale ( $f \pm 1$ ) is noise. In the formula, X denotes the EEG signal and f denotes the frequency.

$$X(f) = fft(X)$$

$$ITR = (\log_2 N + A * \log_2(A) + (1-A) * \log_2(1-A/N-1)) * 60/T \quad (2)$$

$$P_{signal} = \sum_{f_{target}-0.2}^{f_{target}+0.2} |X(f)|^2 \quad (3)$$

$$P_{noise} = \sum_{f_{target}-1}^{f_{target}+1} |X(f)|^2 - P_{signal} \quad (4)$$

$$SNR_{single\_trial} = 10 * \log_{10} \left( \frac{P_{signal}}{P_{noise}} \right) \quad (5)$$

$$SNR_{project} = (\sum_{1block}^{6blocks} \sum_{1trial}^{40trials} SNR_{single\_trial}) / (40*6) \quad (6)$$

## 2.7 Brain network analysis

The whole-brain could be evolved into a complex network while a neuron or a group of nerve cells and the neural connection is regarded as a node and an edge, respectively. Human response to stimulation and emotional behavior might represent the performance of network overlays. Therefore, the research methods for complex networks could be applied to the research of brain science, and the results of network analysis reflect the structural or functional connection between various brain regions that could provide more clues for explaining the deep mechanism. Traditional network analysis methods are canonical correlation analysis (CCA) and directed transfer function (DTF). In this study, the DTF and information flow were computed with the eConnectome Toolbox (Babiloni et al., 2005; Wilke et al., 2010; He et al., 2011) developed by the He Bin team. Define the DTF as  $y_{ij}^2$  and the information flow of region m is computed as the formula below.

$$flow_{in} = \sum_{j=1}^N y_{mj}^2 \quad (8)$$

$$flow_{out} = \sum_{i=1}^N y_{im}^2 \quad (9)$$

Referring to Yan's work (Yan and Gao, 2011), the information flow gain  $\rho$  was also calculated in this study. The information flow gain  $\rho$  is defined as the ratio of the outflow information and the inflow information. The higher the value of the node, the more significant the contribution of the node in the transmission of network information. The smaller the value of  $\rho$ , the lower the contribution of the node in the transfer of network information.

$$\rho = \frac{\text{flow}_{out}}{\text{flow}_{in}} \quad (10)$$

## 2.8 Feedback procedure

This study analyses the global brain information connection network induced by SSVEP using the information flow method. In Fig. 4, it can be seen that there is abundant information flow in the SSVEP state network. The parietal-central (FC1, FCz, FC2, C1, Cz, C2, CP1, CP2) plays an essential role in the induction network while the node size stands for  $\rho$ . The higher the value  $\rho$  of the node, the more significant the contribution of the node in the transmission of network information. Consistent with this, in 2000 Corbetta reported the control effect of the parietal lobe in visual tasks (Corbetta, 2000). Taken together, it suggested that the parietal lobe plays as a central region in visual tasks with attention reorienting effect. The position of the neurofeedback training was selected in the parietal lobe, in which the location with the lowest alpha amplitude was regulated. The electrode selected varies from subject to subject. The training only targets one electrode-position in order to better detect the result.

The NFT system is arranged like Fig. 5. Considering that suspension will require the neuroplasticity of children is stronger, the study selected subjects aged from 7 to 12. In order to attract the interest of the subjects and make them be co-operative, the neurofeedback interactive interface is designed in the form of a game (the interface display like Fig. 6). The program has three options and subjects could select one of them to execute: a. Pacman (A kid eats beans on a given route. Feedback parameters above and below the threshold set corresponding to game pause and progress status respectively). b. Fly the airplane (The aircraft flies on a given route. Feedback parameters above and below the threshold set corresponding to game pause and progress status respectively). c. Racing car (Driving the car on a given route. Feedback parameters above and below the threshold set corresponding to game pause and progress status respectively). Regardless of the form of the game, the subject is always able to keep the EEG parameters above the feedback parameters, thus achieving the effect of neurofeedback training.

The setting of the feedback parameter is divided into two parts, first is the frequency setting and the other is the amplitude setting. Before the formal training, the subjects tested for different feedback frequencies in alpha-band. And the frequency under which the rate of success (neurofeedback training) achieves 60% – 70% is set as the feedback frequency. For the amplitude, it has been found that the amplitude is set to 0.2–0.3 times of the alpha amplitude when subjects are closing their eyes. In this case, the success rate of the training is also 60% – 70%. The feedback process is controlled as Fig. 7 shown. Besides, we adjusted the feedback parameters appropriately according to the success rate (usually increasing the

feedback frequency) as the training goes on. The sampling rate resampling to 250 Hz during calculation while the original sampling rate is 1000 Hz. The length of the calculation window is 2 seconds, and the overlap of the calculation window is 50%. Data update time shall not exceed 1 s.

There are 2000 points used to compute the feedback parameters. The sampling rate is resampled to 250 Hz during calculation while the original sampling rate is 1000 Hz. The length of the calculation window is 2 seconds, and the overlap of the calculation window is 50%. Data update time shall not exceed 1 s. The Welch method is used for the power computation. And there is a bandpass filter (0.5–40 Hz) added to the original data.

Subjects involved in neurofeedback training will sit in front of the computer wearing an EEG cap, gaze at the screen and follow the instructions to complete the task. The system can feedback EEG parameters in real-time and determine whether the respondents are successful. If the feedback is successful (feedback parameters above the threshold), subjects can continue the game. Otherwise, the suspension will require the subject to adjust their status. At this time, the instructor would lead the subject to pay attention to the game. And the subjects should try to adjust state by themselves.

## **2.9 Integrated Visual and Auditory Continuous Performance Test**

The Integrated Visual and Auditory (IVA) continuous performance test (CPT) is a screening tool testing sustained attention (Sandford and Turner, 2000). It was developed by John Sandford (psychologist) and Anne Turner (physician). The initial test consisted of a series of pseudo-randomized auditory and visual stimulation (totally 500 trials) and asked the subject to click on the target they heard or saw. The entire test lasted approximately 20 minutes and our research selected part of the parameters to examine subjects. They were asked to complete some paper quality tables and tested under the guidance of the instructor. The test is a real-time task consisting of repeated auditory and visual stimulations. During the test, the instructor would guide the subject to observe a series of graphics and texts on the scale. Subjects would also listen to a short essay with overt information. The instructor would then ask the participant to give the information required and answer the questions on the scale. The test is used to monitor the effectiveness of neurofeedback training or medication generally.

## **3. Results**

### **3.1 Neurofeedback Training results**

We recruited twenty-four participants, each participant completed 24 training sessions in two months (24 hours in total count). Among these participants, 91.7% were successfully trained (22 of 24). Successfully trained means the alpha-band power of subjects is higher after training. In the Fig. 8, the average alpha-band power ratio of the 24 subjects before and after training is 32.93 and 38.58, respectively. Thus the training brings about 17.16% improvement in the alpha-band power ratio, and the results show a significant difference ( $t = 23, p = 0.00015$ ) by a paired-sample t-test.

## 3.2 Attention test results

Based on the conclusions of a large number of existing studies (Klimesch, 2012), the alpha band is closely related to attention and increase the alpha amplitude could improve attention. In this study, we use the classical attention-operability test (Integrated Visual and Auditory Continuous Performance Test, IVA-CPT) to detect the effect of training on attention. A total of 24 subjects from the experimental group were tested before and after the training, and the test data of 6–15 year- old children in Kim's experiment was used as reference (Kim et al., 2015). Kim's study tested 100 healthy children on the same standard behavioral tests, and we mapped their scores(the original scores range 0-155) to 0–10 for comparison. The statistical results are shown in the following table, each of which is scored from 0–10, with 10 being the best. As the table.1 shown, the mean value of 7 factors before training is  $5.33 \pm 0.97$ , while the index after training is  $6.76 \pm 0.93$ , which shows a significant difference in a paired-sample t-test ( $t = 23$ ,  $p = 0.00172$ ). It indicates that the training brings impressive improvements to visual and auditory attention.

Table 1  
The Attention Quality test results

factor	before training	after training	reference(Kim et al., 2015)
stability of auditory attention	$5.65 \pm 0.93$	$6.82 \pm 0.98$	$6.97 \pm 1.08$
the sensitivity of auditory attention	$5.81 \pm 0.91$	$6.35 \pm 1.12$	$6.64 \pm 1.15$
concentration of visual attention	$5.53 \pm 0.85$	$6.84 \pm 0.91$	$7.19 \pm 1.01$
stability of visual attention	$5.05 \pm 1.23$	$6.67 \pm 0.97$	$7.15 \pm 0.81$
distinction of visual attention	$4.23 \pm 0.95$	$6.42 \pm 0.89$	$6.92 \pm 0.81$
tracking of visual attention	$5.09 \pm 1.12$	$6.75 \pm 1.31$	$6.93 \pm 0.96$
the dynamic quality of attention	$5.95 \pm 0.82$	$7.45 \pm 0.96$	$7.09 \pm 0.93$
Average Score	$5.33 \pm 0.97$	$6.76 \pm 0.93$	$6.98 \pm 0.96$

## 3.3 SSVEP results

Improving SSVEP performance is one of the ultimate goals of this work, and it is also the result supposed to be observed after neurofeedback training. After statistical analysis, the results showed that 87.5% of the subjects (21 of 24) had an improvement with various degrees.

### 3.3.1 Accuracy results

Each participant took part in an SSVEP test of 240 trials within 6 blocks. The average accuracy of 6 blocks was calculated as BCI accuracy (Fig. 9). The results showed that 79.17% of the subjects (19 of 24) improved in some way, while the other five subjects did not improve as they achieved a relatively high accuracy rate (about 90%) in the first test. The average accuracy before training is 78.9% and the figure

after training is 83.6%, which shows a significant difference ( $t = 23, p = 0.0000049$ ). As for the control group, the average accuracy before training is 79% and the figure after training is 79.4%, with no significant differences.

### 3.3.2 ITR results

According to the formula, the average ITR of SSVEP of the 24 participants was 103. After training, the average score of SSVEP of 24 subjects was 119, bringing about 15.6% improvement (see the Fig. 10). After a paired-sample t-test, there was a significant difference ( $t = 23, p = 0.0494$ ). And for the control group, the average ITR after two months is only 103, which is 112 before.

It is noteworthy that three of the subjects do not display an increase of SSVEP ITR because they achieved a high level in the first test, and the performance index declines after training are within a normal fluctuation range.

### 3.3.3 SNR results

SNR is widely used in the engineering field as an indicator to measure the quality of the signal. In this study, 79.17% of the participants (19 of 24) were trained to improve their SSVEP SNR. The average SNR of the subjects was  $-15.2$  dB, and the average SNR of the 24 subjects after training was  $-14.7$  dB which shows a significant difference ( $t = 23, p = 0.0116$ ). For the control group, the average SNR before was  $-15.3$  and it did not change after two months during the same task (see Fig. 11). And the neurofeedback training brings improvement to the SNR of the experimental group by 0.50 dB. From the point of SNR, the training brings 5.8% improvement for the SSVEP signal. Furthermore, the average SNR change in 8 frequency bands (8 Hz-9Hz, 9 Hz-10 Hz, 10 Hz-11 Hz, 11 Hz-12 Hz, 12 Hz-13 Hz, 13 Hz-14 Hz, 14 Hz-15 Hz, 15 Hz-16 Hz) was calculated (see Fig. 12). Taken together, the SNR increases in every frequency band.

We also analyze the SSVEP frequency response and select the response of 8, 9, 10, 11, 12, 13, 14, 15 Hz for all the trials to calculate the topographic map (see Fig. 13). In the SSVEP frequency response topographic map, the experimental group and the control group responded similarly in the first test. However, in the second test, the experimental group have less interference and stronger signal.

We performed a paired t-test on the SSVEP frequency response before and after two months. The p-value obtained was plotted into a statistical topographic map, where the scales range is from 0.2 to 0. That is, the darker region has smaller p-value, indicating that the difference is larger. Vice versa, the lighter has bigger p-value. Above all, these are the locations which have differences: AF3, FC4, CP1, Pz, O2. Notably, the O2 has a significant difference for the experimental group. These results show that the training brings differences to the parietal lobe, the occipital lobe, and the frontal lobe. Furthermore, changes in the occipital region imply that the interference there is suppressed and the SNR increased. The change in the parietal lobe may be related to the enhancement of the control network via neurofeedback regulation. As

for the frontal lobe, the difference may be due to the more concentrated attention of the subjects and the less disruptive interference.

### 3.4 network analysis results

Based on the statistical map of the frequency response difference of the two SSVEP tests, it can be seen that there is a significant difference in the right parietal lobe, occipital region and frontal lobed, so the three locations AF3, FC4, CP1, O2 are selected as the region of interest to analyze the cortex (result shown in Fig. 14 & Fig. 15). Overall, in the connected network of the SSVEP task, the parietal lobe is a hub of information transformation, and there is a large amount of information flowing from the parietal lobe to the occipital lobe and frontal lobe. This result is also consistent with the previous studies (Yan and Gao, 2011).

Table 2  
The node information flow of NFT group (first test/second test)

	<b>AF3</b>	<b>FC4</b>	<b>CP1</b>	<b>O2</b>
AF3	0/0	0/0.01	0.88/0.15	0.01/0
FC4	0.03/0.03	0/0	0.81/0.9	0.01/0
CP1	0.01/0.01	0/0	0/0	0/0
O2	0.04/0.07	0/0.01	0.47/0.9	0/0

Table 3  
The node information flow of control group (first test/second test)

	<b>AF3</b>	<b>FC4</b>	<b>CP1</b>	<b>O2</b>
AF3	0/0	0/0.01	0.81/0.34	0/0
FC4	0.19/0.2	0/0	0.8/0.65	0.01/0
CP1	0.09/0.03	0/0	0/0	0.02/0
O2	0/0.33	0/0	0.84/0.77	0/0

Table 4  
The gain of information flow of node

	<b>experimental group (before/after)</b>	<b>control group (before/after)</b>
AF3	0.08/0.84	0.34/1.49
FC4	0/0.02	0/0.04
CP1	329.63/145.27	22.87/68.64
O2	0.03/0	0.04/0

After calculation, the information of each node of the test group before and after the test was compiled as shown in Table 2 and Table 3, and the flow of information is from row to column. Table 4 suggested that the parietal lobe node CP1 contributes the most in network information transmission. And according to Table 2 and Table 3, the training strengthened the connection of the parietal lobe node to O2 and FC4.

As the information flows from the parietal lobe to the occipital lobe, we further compute the alpha power of the occipital lobe. As shown in the above figures, the occipital lobe alpha power in the task-state was significantly reduced after the neurofeedback training of up-regulating the parietal lobe alpha, while the control group remains normal. The decrease of background alpha power in the occipital lobe reduces the frequency-domain correlation between signal and background noise, which is also consistent with our SNR analysis results.

## 4. Discussion

In accordance with the hypotheses, the trainability of up-regulating NFT in the parietal lobe has been confirmed. The results proved that the training method of this study was conducive to reinforcing the control network and thus enhanced the ability to complete the task. At the same time, the designed test scale also verified the effectiveness of the training on the improvement of attention.

Alpha-band serves as active inhibition (Mathewson et al., 2009; Jensen and Mazaheri, 2010; Klimesch 2012); down-regulation of alpha-band reflects the release from inhibition conversely. The underlying principle of the SSVEP paradigm is that a stimulus target flickers with a fixed frequency induces an evoked response with stable frequency characteristics in the occipital lobe. Enhancement of alpha-band activity in the parietal lobe inhibits task-irrelevant information give rise to attention (As shown in Table 1), SNR and the SSVEP performance. However, there has been no clear correspondence founded among the increase of alpha-band power, SNR, and ITR in data analysis. The finding represented that there may be some unknown complex factors in the attention network.

### 4.1 Comparison of similar work and Neural mechanism

Some previous research was similar to our study (Hanslmayr et al., 2005; Vernon, 2005; Zoefel et al., 2011; Lee, 2019). Benedikt reported that up-regulating the amplitude of upper-alpha on the parieto-occipital lobe to enhance cognitive ability received a positive result. Benedikt attributed this success to the close relationship between alpha-band and cognition without explanation of how the alpha-band was associated with cognition. Another work was based on alpha down-regulating neurofeedback training to improving the SSVEP performance (Wan et al., 2016). Since Wan's work seems to conflict with the work of this study, it is worthwhile to discuss the difference between the two works in detail. In the project of Wan, a two-day alpha down-regulating feedback neurofeedback training on the occipital region was conducted on 20 subjects, and it was found that this training affected SSVEP performance. Regulating different lobe is one of the distinctions between our experiment and Wan's. This study focuses on the parietal lobe while the occipital lobe was regulated in Wan's research – however, two research access to the same goal that enhances the SSVEP-based BCI performance through different aspects.

In the SSVEP test of Wan, 7.05, 7.5, 8, 8.57, 9.23, 10, 10.9, 12, 13.33, and 15 (Hz) were chosen as the stimulation frequency. The reason for this choice is that SSVEP response most active in the low frequency band (8-16Hz). Since the frequency range selected of this method includes 8–12 (Hz), background alpha-band could regard as a natural interference. The implementation principle of SSVEP-based BCI relies on detecting the response of the stimulation frequency of the occipital region to determine the target. Since that, the BCI accuracy is much dependent on whether the frequency response is precise. As is known to all, the alpha-band is usually defined as 8–12 (Hz). In the view of the concept of the individual alpha band, the alpha-band could roughly extend between 7 and 13. The alpha-band component of spontaneous background EEG could interfere with the identification and judgment of SSVEP-based BCI. Therefore, the work of Wan was to down-regulate the alpha component of the occipital region through NFT to weaken the interference, which achieved the purpose of improving SSVEP-based BCI performance. More interestingly, analysis of our data showed that the background alpha component (Task State) of the occipital lobe also decreased after modulating in the parietal lobe (result shown in Fig. 16). Consistent with our result, Wan decrease alpha amplitude in the occipital lobe to reduce interference and get higher SNR and better performance. Another worth noting was that the method of Wan brings improvement in the SNR of frequency band near the alpha-band (8 Hz-12 Hz). In our work, it has been found that improving the alpha amplitude of the parietal lobe brought SNR improvement to each frequency band (8 Hz-16 Hz). Differences have not observed in a specific frequency band, and the macro-control function of the parietal lobe is confirmed again by this conclusion.

In the previous research of SSVEP in our laboratory, it was observed that the SSVEP effect was strictly related to the attention of the subjects. This finding is well in line with common sense that people are more efficient and effective when they are focused on their tasks. The alpha-band is closely linked to attention because it plays a role in suppressing task-related noise. Therefore, increase the alpha amplitude of the parietal lobe brings attention improvement and further enhances the quality of the SSVEP signal. It is worth noting that although two studies have taken the opposite approach (up-regulate and down-regulate), NFT has been applied to different brain lobes and achieve the same purpose. Based on past reports and a large number of observations (Matsumoto and Tanaka, 2004; Lakatos et al., 2005),

neuronal systems in the brain can be divided into control networks and execution networks in which the oscillations of various frequencies play different roles. That is: low-frequency oscillation (theta/alpha) plays the role of monitoring, regulation and information transmission, while high-frequency oscillation (beta) serves as information processing and function execution. From this point of view, Wan's works and ours regulating the functional network and control network, respectively. In fact, the human brain is not merely a passive response to the stimulus, but a top-down processing mechanism with macro-control. In this mechanism, the flow of information is top-down and distinguishes between control and function, and the overall control also determines the function of the different regions (Nunez, 2000; Engel et al., 2001). Some research evidence supported the view that involvement of the alpha-band in the process by which the human brain converts input visual and auditory information into behavior, from control to functional differentiation (Jaime, 2005; Thut et al., 2006; Sauseng et al., 2006).

## **4.2 More description about controls and functional**

Prior research has reported that the control network and functional network may exist and provided a lot of direct or indirect evidence. Foxe and Bauer recommend models implicating parieto-occipital areas prominently in the directing and maintenance of visual attention (Foxe et al., 1998; Bauer, 2006). As well as, the results indicated that the network of control and functional might not be wholly separated. In the corresponding difference analysis of SSVEP data before and after training (see Fig. 10), it can be seen that neurofeedback training affects the parietal lobe, occipital lobe, and frontal lobe. The alteration takes place in the occipital lobe and the frontal lobe is due to the increase of attention and the decrease of signal noise. Simultaneously, the differences observed in the parietal lobe advocates that the NFT enhances the capacity of the control network. In Srinivasan's fMRI studies (Srinivasan, 2007), it was also found that some of the occipital voxels were positively correlated to the frontal voxels forming a large-scale functional network when visual input. Coupled with the parietal lobe push forward an immense influence on regulating of visual stimuli, we could suggest that the human brain responds to visual stimuli by arousing a parietal-occipital-forehead control/ functional network. Moreover, parietal-occipital-forehead region work as an inseparable system.

The outcome of network connection analysis also verifies the inference that the frontal lobe, parietal lobe and occipital lobe work in a network within the SSVEP visual task. The parietal lobe serves as the sole hub of information output and transmission. In Table 2 and Table 3, it can be seen that the information output of the parietal lobe (CP1 to O2, CP1 to FC4) is increased after training in the NFT group, which also confirm the enhancement of the control capability of the parietal lobe.

## **4.3 Worth and innovation**

In our work, a total of 24 children have arranged a neurofeedback training for two months. After investigations, we found that 1–2 months seems to be the shortest period for NFT which could produce a stable effect. Some previous research suggests that the resting alpha went back to the initial level after a 20–40 minutes rest in alpha-band NFT (Ros et al., 2013; Kluetsch et al., 2014) so that the effect of short-term NFT is unstable. Although the EEG record that used to calculate the alpha band power ratio was

collected ten days after the last training in this experiment, the outcome showed that 22 of the 24 subjects remain improvement of various degrees. The upshot suggests that the methods of training in this research are stable and might have a long-term effect, which has not been reported in many studies (Heinrich et al., 2007; Gruzelier and John, 2013; Gruzelier, 2014). Two branches with the most research potential of neural engineering are the interpretation of brain information and neuromodulation. Especially the regulating of neural activity is one of the keys to realizing brain-computer interaction in the future. In order to realize brain-computer interaction and the enhancement of human brain function, stable and sustainable regulating is crucial. Short-term and unstable modulating methods may bring some unexpected trouble.

Despite people's extreme desire to know more about the human brain, breakthrough in brain science is driven by strictly prohibit prudence experiments. This also requires a controllable and stable experimental design to avoid any possible damage and risk. The choice of children subjects in this study undoubtedly increases the difficulty of research. Nonetheless, take the young brains are more neuroplasticity into consideration, such an attempt makes sense. In most studies on neurofeedback training, the choice of subjects is adults (Angelakis et al., 2007; Zotev et al., 2014), and research on children is relatively rare.

## 5. Conclusions

In this work, we found a kind of neurofeedback training method and got the following conclusions. 1) The effect of neurofeedback training could be stable for a long time. 2) Neurofeedback training to improve parietal alpha oscillation could improve attention by suppressing interference. 3) This neurofeedback training could improve the SNR and ITR of the SSVEP signal. 4) This training method could improve SSVEP-based BCI performance. 5) The working mechanism of the brain may include control network and functional network and could be adjusted separately.

## Abbreviations

BCI  
Brain-computer interface; NTF:Neurofeedback training;  
SSVEP  
steady-state visual evoked potential; SNR:signal-to-noise ratio;  
ITR  
information transfer rate; EEG:electroencephalogram;  
ERD  
event-related desynchronization; FBCCA:filter bank canonical correlation analysis  
TRCA  
task-related component analysis

## Declarations

## **Ethics Approval and Consent to Participate**

The written consent form was received from all of the participants' guardians. And this project is reviewed by the Ethics Committee of the Tsinghua University School of Medicine (Protocol number 2019006 approved on 3/4/2019).

## **Consent for publication**

Consent to publish was obtained from their parent or legal guardian.

## **Availability of supporting data**

The raw/processed data required to reproduce these findings cannot be shared at this time as the data also forms part of an ongoing study. We could consider publishing some valuable data in case of acceptance.

## **Competing interests**

The authors declare that they have no competing interests.

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## **Authors' contributions**

Sun contributed to the whole research process, including experiment design, data collection, result analysis and article writing. He participated in data collection and helped to improve and polish the article. As the corresponding author, professor Gao guided the research and the arrangement of the article. He also revising the manuscript content critically and checked the quality of the research. All authors read and approved the final manuscript.

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## Authors' information

<sup>a</sup>Department of Biomedical Engineering, Tsinghua University, China. <sup>b</sup>Department of Life Sciences, Tsinghua University, China. <sup>c</sup>Tsinghua-Peking Center for Life Sciences, McGovern Institute for brain Research, China. Address correspondence to Xiaorong Gao, Department of Biomedical Engineering, Tsinghua University, Beijing 100084, China. Email: gxr-dea@tsinghua.edu.cn

## References

1. Angelakis, E., Stathopoulou, S., Frymiare, J. L., Green, D. L., & Kounios, J.. (2007). Eeg neurofeedback: a brief overview and an example of peak alpha frequency training for cognitive enhancement in the elderly. *The Clinical Neuropsychologist*,21(1), 110-129.
2. Arns, M., de Ridder, S., Strehl, U., Breteler, M., and Coenen, A. (2009). Efficacy of neurofeedback treatment in ADHD: the effects on inattention, impulsivity and hyperactivity: a meta-analysis. *EEG Neurosci.* 40, 180–189.
3. Babiloni, F., Cincotti, F., Babiloni, C., Carducci, F., Mattia, D., & Astolfi, L., et al. (2005). Estimation of the cortical functional connectivity with the multimodal integration of high-resolution EEG and fMRI data by directed transfer function. *Neuroimage*, 24(1), 118-131.
4. Berger, H. (1929). Uber das Elektrenkephalogramm des Menschen (On the EEG in human). *Archiv fur Psychiatrie und Nervenkrankheiten.*, 87: 527–570.
5. Bauer, & M. (2006). Tactile spatial attention enhances gamma-band activity in somatosensory cortex and reduces low-frequency activity in parieto-occipital areas. *Journal of Neuroscience*, 26(2), 490-501.
6. Bruno, B.-V.; Reyes-Ramirez Diego, F.; Blanca, T.-C.; Alvaro, A.-R.; Gonzalo, S.-V.J. (2017). Neurofeedback training system with audiovisual stimuli for the attention state induction during cognitive processes. *International Conference on Electrical Engineering, Computing Science and Automatic Control(CCE)*. pp 4.
7. Busch, N. A., Dubois, J., & Vanrullen, R. (2009). The phase of ongoing EEG oscillations predicts visual perception. *Journal of Neuroscience*, 29(24), 7869.
8. Buzsaki, G. (2004). Neuronal oscillations in cortical networks. *Science*, 304(5679), 1926-1929.
9. Buzsaki, Gyoergy, & Moser, E. I. (2013). Memory, navigation and theta rhythm in the hippocampal-entorhinal system. *Nature Neuroscience*, 16(2), 130-138.
10. Canolty, R. T., Edwards, E., Dalal, S. S., Soltani, M., Nagarajan, S. S., & Kirsch, H. E., et al. (2006). High gamma power is phase-locked to theta oscillations in human neocortex. *Science*, 313.
11. Chen, X. , Chen, Z. , Gao, S. , & Gao, X. (2014). A high-itr ssvep-based bci speller. *Brain-Computer Interfaces*, 1(3-4), 181-191.

12. Chen, X. , Wang, Y. , Nakanishi, M., Gao, X. , Jung, T. P., & Gao, S.. (2015). High-speed spelling with a noninvasive brain-computer interface. *Proceedings of the National Academy of Sciences*, 201508080.
13. Chen, X. , Wang, Y. , Gao, S., Jung, T. P., & Gao, X. (2015). Filter bank canonical correlation analysis for implementing a high-speed ssvep-based brain-computer interface. *Journal of Neural Engineering*, 12(4), 046008.
14. Collura, & Thomas, F.. (2002). Application of repetitive visual stimulation to EEG neurofeedback protocols. *Journal of Neurotherapy*, 6(2), 47-70.
15. Corbetta, M.. (2000). Voluntary orienting is dissociated from target detection in human posterior parietal cortex. *Nature Neuroscience*, 3.
16. Di Pellegrino, G. Clock-drawing in a case of left visuospatial neglect: a deficit of disengagement? *Neuropsychologia* 33, 353–358 (1995).
17. Engel, A. K., Fries, P., & Singer, W.. (2001). Dynamic predictions: oscillations and synchrony in top-down processing. *Nature Reviews Neuroscience*, 2(10), 704-716.
18. Ergenoglu, T. , Demiralp, T. , Bayraktaroglu, Z. , Ergen, M. , Beydagi, H. , & Uresin, Y. . (2004). Alpha rhythm of the eeg modulates visual detection performance in humans. *Cognitive Brain Research*, 20(3), 376-383.
19. Foxe, J. J., Simpson, G. V., & Ahlfors, S. P. (1998). Parieto-occipital similar to 10 hz activity reflects anticipatory state of visual attention mechanisms. *NeuroReport*, 9(17), 3929-3933.
20. Friedrich, F. J., Egly, R., Rafal, R. D. & Beck, D. Spatial attention deficits in humans: a comparison of superior parietal and temporo-parietal junction lesions. *Neuropsychology* 12, 193–207 (1998).
21. Gruzelier, J. H. . (2013). Eeg-neurofeedback for optimising performance. i: a review of cognitive and affective outcome in healthy participants. *Neuroscience & Biobehavioral Reviews*, 44, 124-141.
22. Gruzelier, & John, H. . (2014). Eeg-neurofeedback for optimising performance. ii: creativity, the performing arts and ecological validity. *Neuroscience & Biobehavioral Reviews*, 44(Sp. Iss. SI), 142-158.
23. Halligan, P. W. & Marshall, J. C. Toward a principled explanation of unilateral neglect. Special Issue: The cognitive neuropsychology of attention. *Cognit. Neuropsychol.* 11, 167–206 (1994).
24. Hanslmayr, S., Sauseng, P., Doppelmayr, M., Schabus, M., & Klimesch, W. (2005). Increasing individual upper alpha power by neurofeedback improves cognitive performance in human subjects. *Applied Psychophysiology and Biofeedback*, 30(1), 1-10.
25. Hanslmayr, S. et al. (2005) Visual discrimination performance is related to decreased alpha amplitude but increased phase locking. *Lett.* 375, 64–68
26. He, B., Dai, Y. , Astolfi, L., Babiloni, F., Yuan, H., & Yang, L.. (2011). Econnectome: a matlab toolbox for mapping and imaging of brain functional connectivity. *Journal of Neuroscience Methods*, 195(2), 261-269.

27. Heinrich, H., Gevensleben, H., & Strehl, U.. (2007). Annotation: neurofeedback-train your brain to train behaviour. *Journal of Child Psychology and Psychiatry*, 48(1), 14.
28. Howells, F. M., Temmingh, H. S., Hsieh, J. H., Van Dijken, A. V. , Baldwin, D. S., & Stein, D. J.. (2018). Electroencephalographic delta/alpha frequency activity differentiates psychotic disorders: a study of schizophrenia, bipolar disorder and methamphetamine-induced psychotic disorder. *Translational Psychiatry*, 8(1), 75.
29. Heilman, K. M., Watson, R. T. & Valenstein, E. in *Clinical Neuropsychology* (eds. Heilman, K. M. & Valenstein, E.) 243–293 (Oxford, New York, 1985).
30. Hughes, S. et al. (2011) Thalamic gap junctions control local neuronal synchrony and influence macroscopic oscillation amplitude during
31. EEG alpha rhythms. *Psychol.* 2, 193
32. Jaime A. Pineda. (2005). The functional significance of mu rhythms: translating “seeing” and “hearing” into “doing”. *Brain Research Reviews*, 50(1), 57-68.
33. Jensen, O., & Mazaheri, A.. (2010). Shaping functional architecture by oscillatory alpha activity: gating by inhibition. *Frontiers in Human Neuroscience*, 4(article 186), 186.
34. Jokisch, D. . (2007). Modulation of gamma and alpha activity during a working memory task engaging the dorsal or ventral stream. *J Neurosci*, 27.
35. Kim, J. W., Lee, Y. S., Han, D. H., Min, K. J., Kim, D. H., & Lee, C. W.. (2015). The utility of quantitative electroencephalography and integrated visual and auditory continuous performance test as auxiliary tools for the attention deficit hyperactivity disorder diagnosis. *Clinical Neurophysiology*, 126(3), 532-540.
36. Klimesch, W.. (1999). EEG alpha and theta oscillations reflect cognitive and memory performance: a review and analysis. ,29(2-3), 0-195.
37. Klimesch, W, Sauseng P, Hanslmayr S (2007) EEG alpha oscillations: the inhibition-timing hypothesis. *Brain Res Rev* 53: 63–88.
38. Klimesch, W.. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in Cognitive Sciences*, 16(12), 606-617.
39. Kluetsch R C, Ros T, Théberge J, Frewen P A, Calhoun V D, Schmahl C, Jetly R and Lanius R A 2014 Plastic modulation of PTSD resting-state networks and subjective wellbeing by EEG neurofeedback *Acta Psychiatr. Scand.* 130 123–36
40. Lakatos P, Shah AS, Knuth KH, Ulbert I, Karmos G, Schroeder CE. 2005. An oscillatory hierarchy controlling neuronal excitability and stimulus processing in the auditory cortex. *J. Neurophysiol.*94(3):1904–11
41. Iaccarino, H. F. (2016). Gamma frequency entrainment attenuates amyloid load and modifies microglia. *Nature*.
42. Lee, Y. J., Kim, H. G., Cheon, E. J., Kim, K., & Koo, B. H. . (2019). The analysis of electroencephalography changes before and after a single neurofeedback alpha/theta training

- session in university students. *Applied Psychophysiology and Biofeedback*(533).
43. Lopes da Silva, F.H. et al. (1973) Organisation of thalamic and cortical alpha rhythms: spectra and coherences. *Electroencephalogram*.
  44. *Neurophysiol.* 35, 627–639
  45. Lo´rincz, M. et al. (2009) Temporal framing of thalamic relay-mode firing by phasic inhibition during the alpha rhythm. *Neuron* 63,
  46. 683–696
  47. Manyakov N V, Chumerin N, Robben A, Combaz A, van Vliet M and Van Hulle M M 2013 Sampled sinusoidal stimulation profile and multichannel fuzzy logic classification for monitor-based phase-coded SSVEP brain–computer interfacing, *Journal of Neural Engineering*, 10, 036011
  48. Mathewson, K. E., Gratton, G., Fabiani, M., Beck, D. M., & Ro, T. (2009). To see or not to see: prestimulus phase predicts visual awareness. *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience*, 29(9), 2725-2732.
  49. Matsumoto, K. , & Tanaka, K. . (2004). Neuroscience. conflict and cognitive control. *Science*, 303(5660), 969-70.
  50. Mayeli, A., Misaki, M., Zotev, V., Tsuchiyagaito, A., Al Zoubi, O., Phillips, R., Smith, J., Stewart, J.L., Refai, H., Paulus, M.P., & Bodurka, J. (2019). Self-regulation of ventromedial prefrontal cortex activation using real-time fMRI neurofeedback-Influence of default mode network. *Human Brain Mapping*.
  51. Mayra, B. V., & Maurits, N. M. . (2018). Stimuli and feature extraction algorithms for brain-computer interfaces: a systematic comparison. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 1-1.
  52. Mesulam, M. M. A cortical network for directed attention and unilateral neglect. *Neurol.*10, 309–315 (1981).
  53. Morgan, S. T., Hansen, J. C., & Hillyard, S. A.. (1996). Selective attention to stimulus location modulates the steady-state visual evoked potential. *Proceedings of the National Academy of Sciences*, 93(10), 4770-4774.
  54. Morrow, L. A. & Ratcliff, G. The disengagement of covert attention and the neglect syndrome. *Psychobiology*16, 261–269 (1988).
  55. Nakanishi, M., Wang, Y. , Chen, X. , Wang, Y. T., Gao, X. , & Jung, T. P. (2017). Enhancing detection of ssveps for a high-speed brain speller using task-related component analysis. *IEEE Transactions on Biomedical Engineering*, 1-1.
  56. Neuper C and Pfurtscheller G 2010 Neurofeedback training for BCI control *Brain-Computer Interfaces* (Berlin: Springer) pp 65–78
  57. Nicoletis, M.A.L. and Fanselow, E.E. (2002) Thalamocortical optimization of tactile processing according to behavioural state. *Neurosci.* 5, 517–523

58. Nunez, P. L.. (2000). Toward a quantitative description of large-scale neocortical dynamic function and eeg. *Behavioral & Brain Sciences*, 23(3), 371-398.
59. Nunez, P. L., Wingeier, B. M., & Silberstein, R. B.. (2001). Spatial-temporal structures of human alpha rhythms: theory, microcurrent sources, multiscale measurements, and global binding of local networks., *Human Brain Mapping*, 13(3), 125-164.
60. Ordikhani-Seyedlar, M., Sorensen, H. B. D., Kjaer, T. W., Siebner, H. R., & Puthusserypady, S.. (2014). SSVEP-modulation by covert and overt attention: novel features for bci in attention neuro-rehabilitation. *Conf Proc IEEE Eng Med Biol Soc*, 2014, 5462-5465.
61. Papoutsis, M., Weiskopf, N., Langbehn, D., Reilmann, R., Rees, G., & Tabrizi, S. J.. (2017). Stimulating neural plasticity with real-time fMRI neurofeedback in Huntington's disease: a proof of concept study. *Human Brain Mapping*, 39-3, 1339-1353
62. Posner, M. I., Walker, J. A., Friedrich, F. J. & Rafal, R. D. Effects of parietal injury on covert orienting of attention. *Neurosci*.4, 1863–1874 (1984).
63. Ros T, Théberge J, Frewen P A, Kluetsch R, Densmore M, Calhoun V D and Lanius R A 2013 Mind over chatter: plastic up-regulation of the fMRI salience network directly after EEG neurofeedback. *Neuroimage*, 65 324–35
64. Sandford, J. A., & Turner, A. (2000). Integrated visual and auditory continuous performance test manual. *Richmond, VA: Brain Train.*
65. Sauseng, P., Klimesch, W., Stadler, W., Schabus, M., & Birbaumer, N. (2006). A shift of visual spatial attention is selectively associated with human EEG alpha activity. *European Journal of Neuroscience*, 22(11), 2917-2926.
66. Schafer, RJ, Moore, T..(2011) Selective Attention from Voluntary Control of Neurons in Prefrontal Cortex. *Science*, 332(6037), 1568-1571.
67. Schmid, M.C. et al. (2012) Thalamic coordination of cortical communication. *Neuron* 75, 551–552
68. Sonuga-Barke EJS, Brandeis D, Cortese S, Daley D, Ferrin M, Holtmann M, Stevenson J, Danckaerts M, Van der Oord S, Dopfner M, Dittmann RW, Simonoff E, Zuddas A, Banaschewski T, Buitelaar J, Coghill D, Hollis C, Konofal E, Lecendreux M, Wong ICK, Sergeant J (2013) Nonpharmacological interventions for ADHD: systematic review and meta-analyses of randomized controlled trials of dietary and psychological treatments. *Am J Psychiatry* 170:275–289
69. Srinivasan, R., Fornari, E., Knyazeva, M. G., Meuli, R., & Maeder, P.. (2007). fMRI responses in medial frontal cortex that depend on the temporal frequency of visual input. *Experimental Brain Research*, 180(4), 677-691.
70. Thut, G., Nietzel, A., Brandt, S., & Pascual-Leone, A.. (2006). Alpha-band electroencephalographic (eeg) activity over occipital cortex indexes visuospatial attention bias and predicts visual target detection. *Journal of Neuroscience*, 26(37), 9494-9502.
71. Van Praag, H. . (2005). Exercise enhances learning and hippocampal neurogenesis in aged mice. *J Neurosci*, 25.

72. Vernon, D., Egner, T., Cooper, N., Compton, T., Neilands, C., & Sheri, A., et al. (2003). The effect of training distinct neurofeedback protocols on aspects of cognitive performance. *International Journal of Psychophysiology*, 47(1), 0-85.
73. Vernon, D. J.. (2005). Can neurofeedback training enhance performance? an evaluation of the evidence with implications for future research. *Applied Psychophysiology and Biofeedback*, 30(4), 347-364.
74. Wan, F., Da Cruz, J. N., Nan, W., Wong, C. M., Vai, M. I., & Rosa, A.. (2016). Alpha neurofeedback training improves ssvep-based bci performance. *Journal of Neural Engineering*, 13(3), 036019.
75. Wilke, C., Drongelen, W. V., Kohrman, M., & He, B. . (2010). Neocortical seizure foci localization by means of a directed transfer function method. *Epilepsia*, 51(4), 564-572.
76. Yan, Z. , & Gao, X.. (2011). Functional connectivity analysis of steady-state visual evoked potentials. *Neuroscience Letters*, 499(3), 199-203.
77. Zhao, L., Wu, W., Liang, Z. , & Hu, G.. (2009). Changes in EEG measurements in intractable epilepsy patients with neurofeedback training. *Progress in Natural Science*, 19(11), 1509-1514.
78. Zoefel, B., René J. Huster, & Herrmann, C. S. (2011). Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance. *Neuroimage*, 54(2), 1427-1431.
79. Zotev, V., Phillips, R., Yuan, H., Misaki, M., & Bodurka, J.. (2014). Self-regulation of human brain activity using simultaneous real-time fMRI and EEG neurofeedback. *NeuroImage*, 85, 985-995.

## Figures

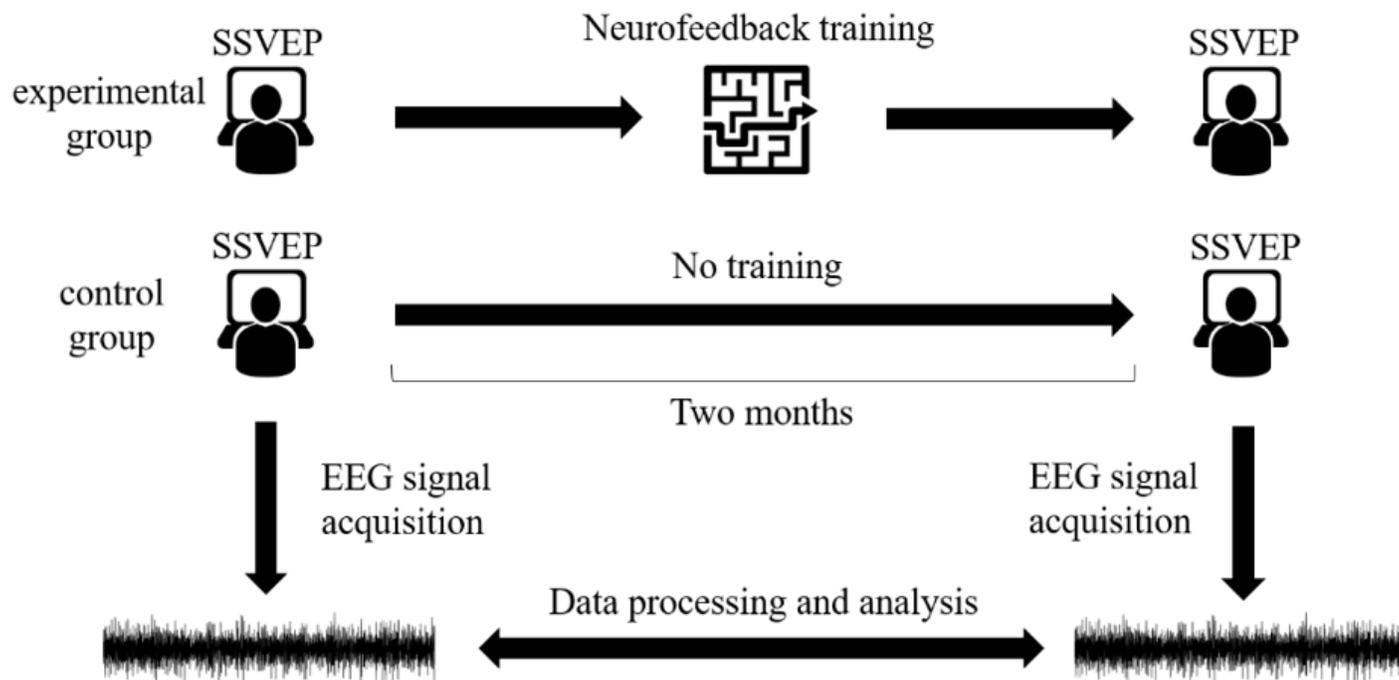


Figure 1

Protocol description of pre- and post-training for the NFT group and non-NFT group. The entire experimental process includes data acquisitions, feedback training, and data processing. The control group and the experimental group are only different from whether or not feedback training was performed.

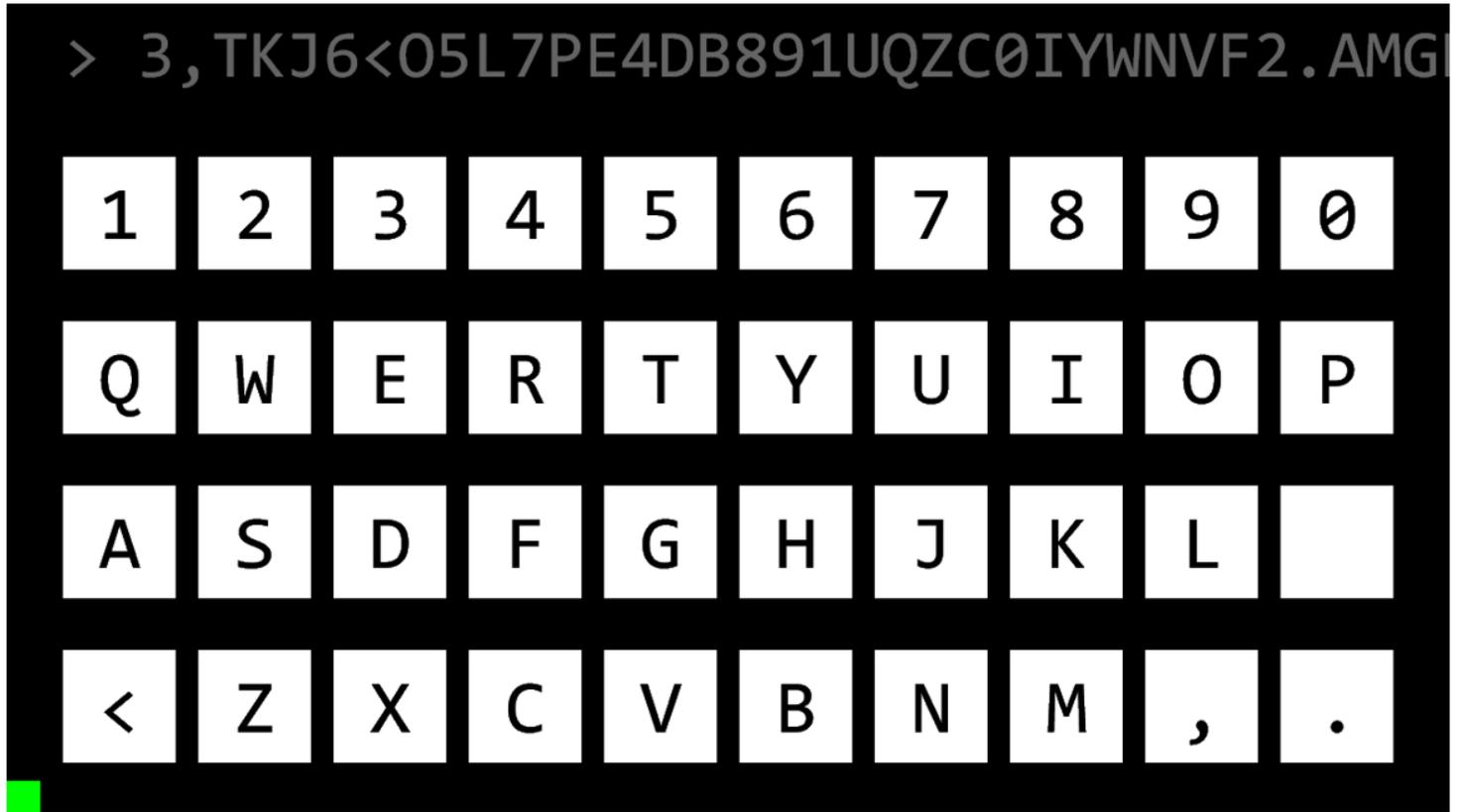


Figure 2

The SSVEP stimulation interface consists of 40 stimulus target blocks on the screen, which respectively represent A-Z with a total of 26 letters, 0-9 total ten digits, spaces, commas, periods, and backspace keys.

8Hz $0\pi$	8.8Hz $0\pi$	9.6Hz $0\pi$	10.4Hz $0\pi$	11.2Hz $0\pi$	12Hz $0\pi$	12.8Hz $0\pi$	13.6Hz $0\pi$	14.4Hz $0\pi$	15.2Hz $0\pi$
8.2Hz $0.5\pi$	9Hz $0.5\pi$	9.8Hz $0.5\pi$	10.6Hz $0.5\pi$	11.4Hz $0.5\pi$	12.2Hz $0.5\pi$	13Hz $0.5\pi$	13.8Hz $0.5\pi$	14.6Hz $0.5\pi$	15.4Hz $0.5\pi$
8.4Hz $1\pi$	9.2Hz $1\pi$	10Hz $1\pi$	10.8Hz $1\pi$	11.6Hz $1\pi$	12.4Hz $1\pi$	13.2Hz $1\pi$	14Hz $1\pi$	14.8Hz $1\pi$	15.6Hz $1\pi$
8.6Hz $1.5\pi$	9.4Hz $1.5\pi$	10.2Hz $1.5\pi$	11Hz $1.5\pi$	11.8Hz $1.5\pi$	12.6Hz $1.5\pi$	13.4Hz $1.5\pi$	14.2Hz $1.5\pi$	15Hz $1.5\pi$	15.8Hz $1.5\pi$

Figure 3

SSVEP frequency and phase table, the frequency and phase of the stimulation were set according to the paradigm given in the picture.

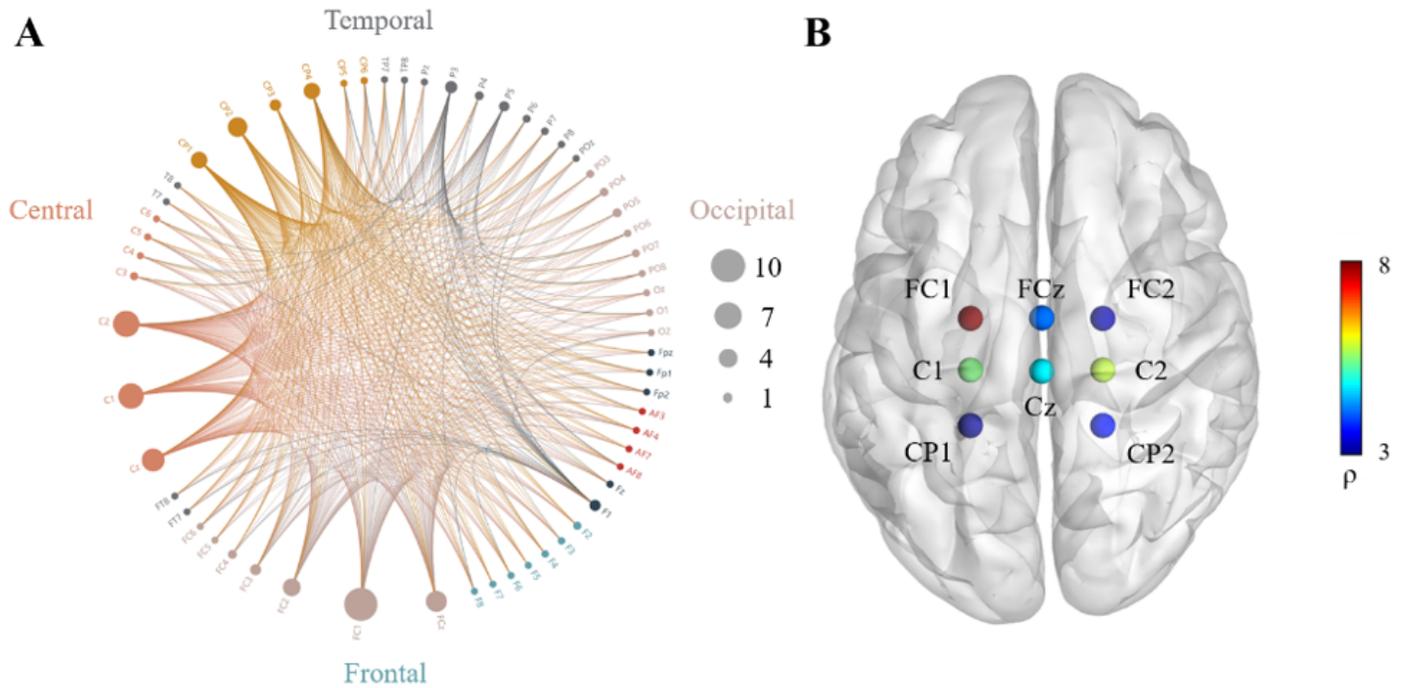
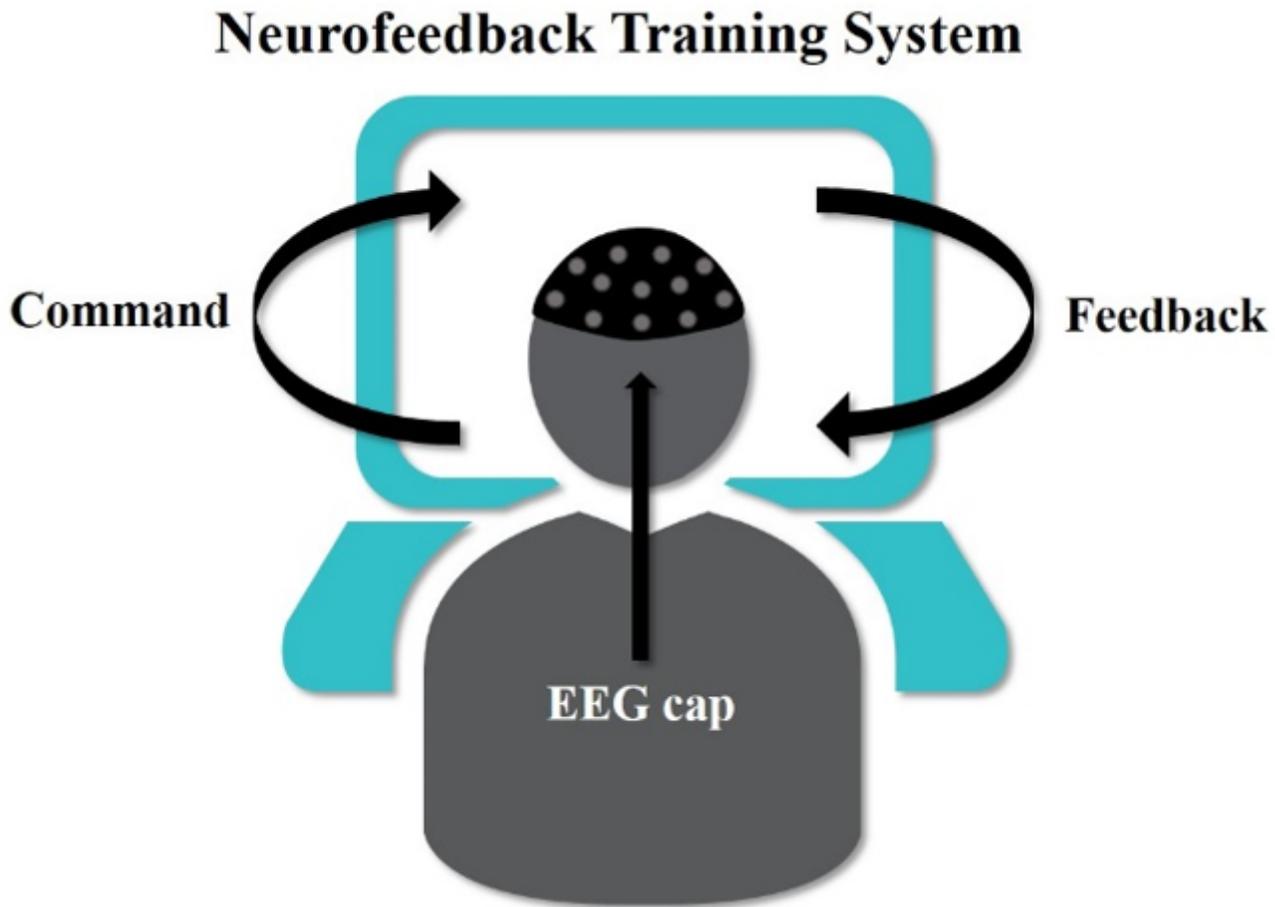


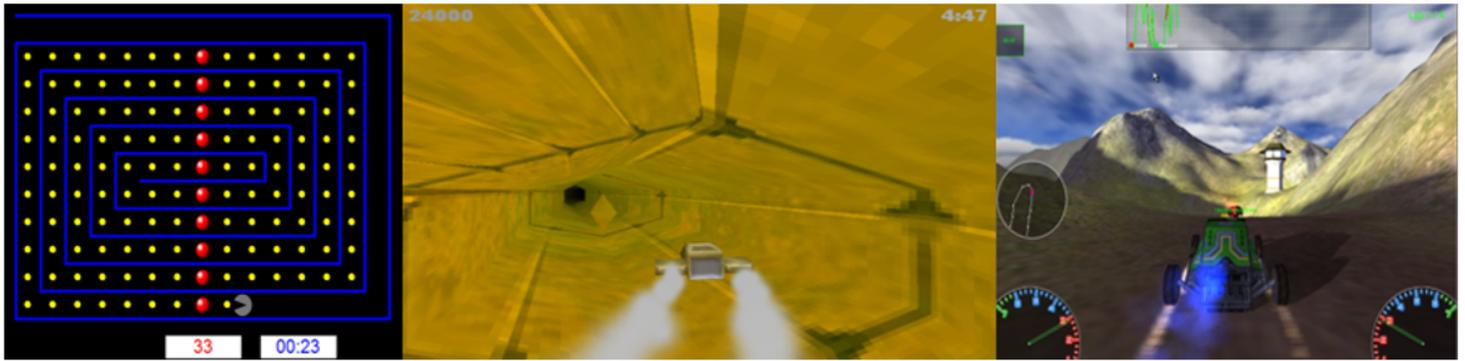
Figure 4

The figure shows the global information flow of functional connectivity in the SSVEP task. In figure A, the node size is represented by  $\rho$  and the region is distinguished by color. It can be seen that the eight leads of the parietal lobe play a vital role in the information network throughout the network. Figure B shows the location of the core nodes of the parietal lobe on the cortex.



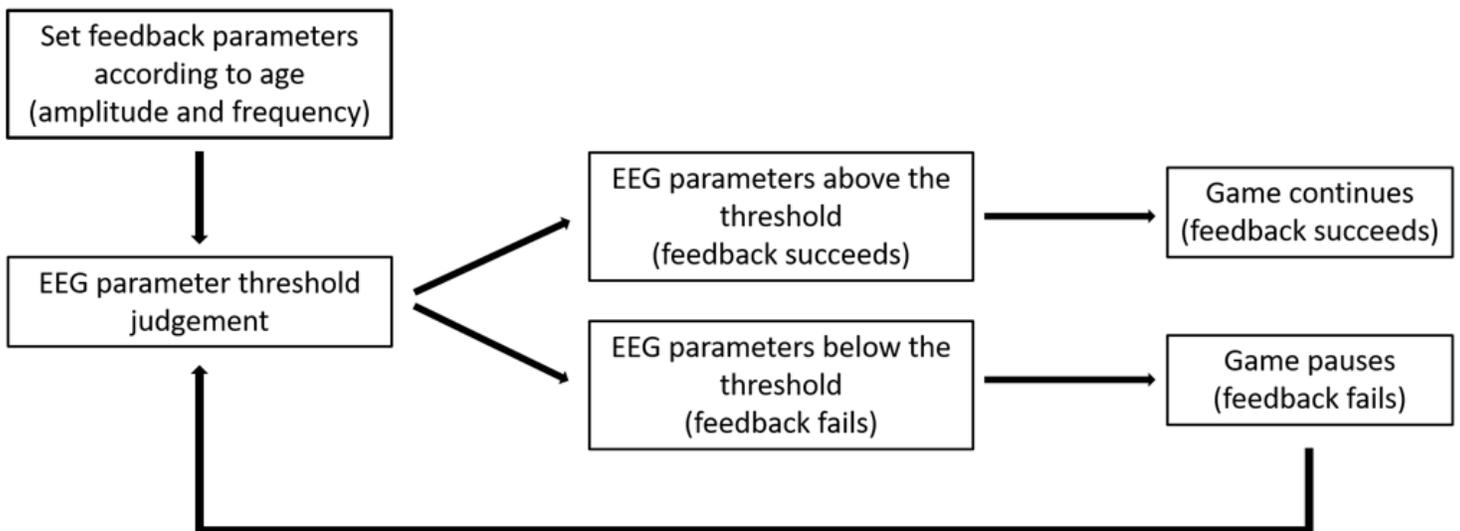
**Figure 5**

The feedback system. The subject wears an EEG cap to sit in front of the computer and looks at the feedback stimulation program, while the computer receives the subject's EEG data in real-time and calculates their feedback parameters. The calculated feedback parameters control the feedback procedure, and the effect is resubmitted to the subject. Repeated loops of this process constitute a complete neurofeedback training system



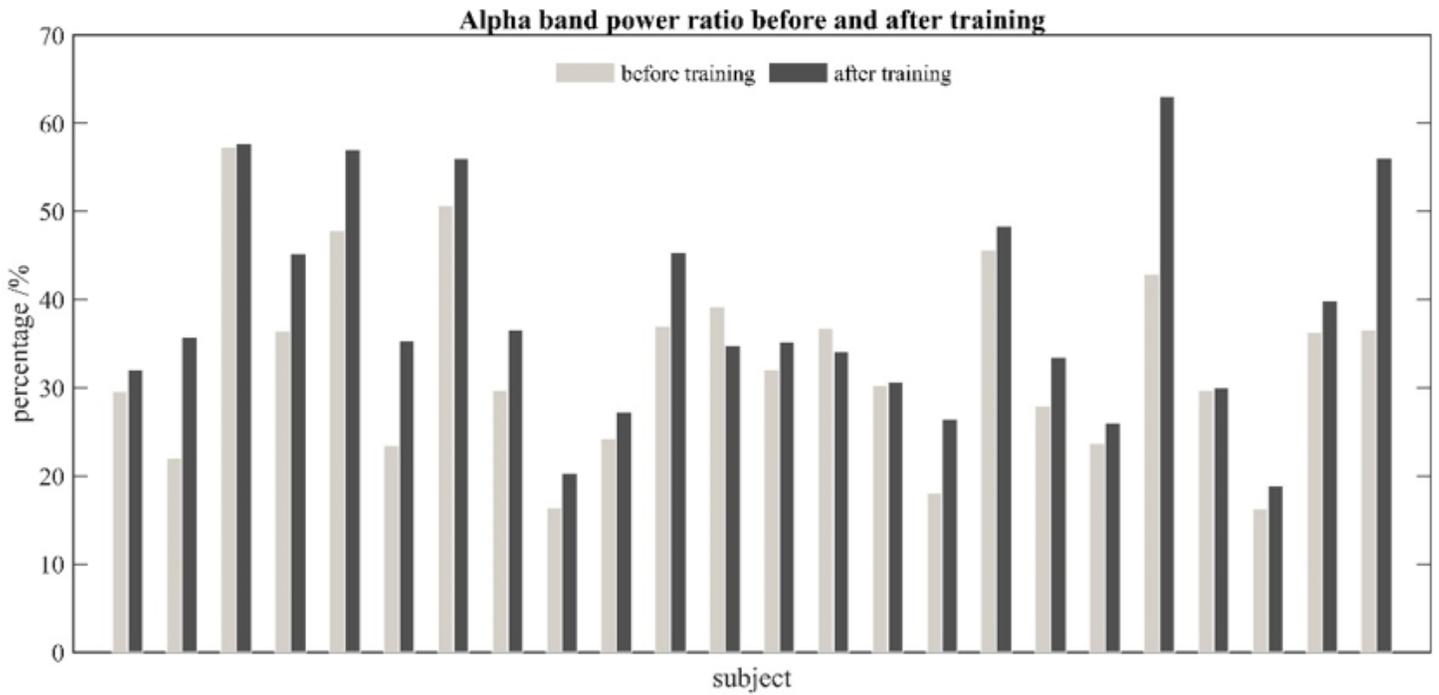
**Figure 6**

The feedback training interface. There are three alternative modes for the game interface designed to excite the interest of the participants. (a) Pacman. (b) Fly the airplane. (c) Racing car.

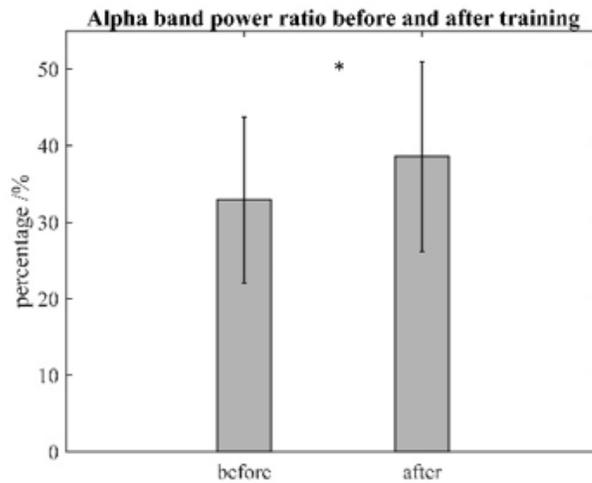


**Figure 7**

The neurofeedback training process is shown in the figure. The real-time EEG parameters of the subject are collected and compared with the set threshold. If the EEG parameter is above the threshold, the game continues. Otherwise, the game suspends, and the subject should adjust the state as required. The entire process circulates to finally achieve the training goal.



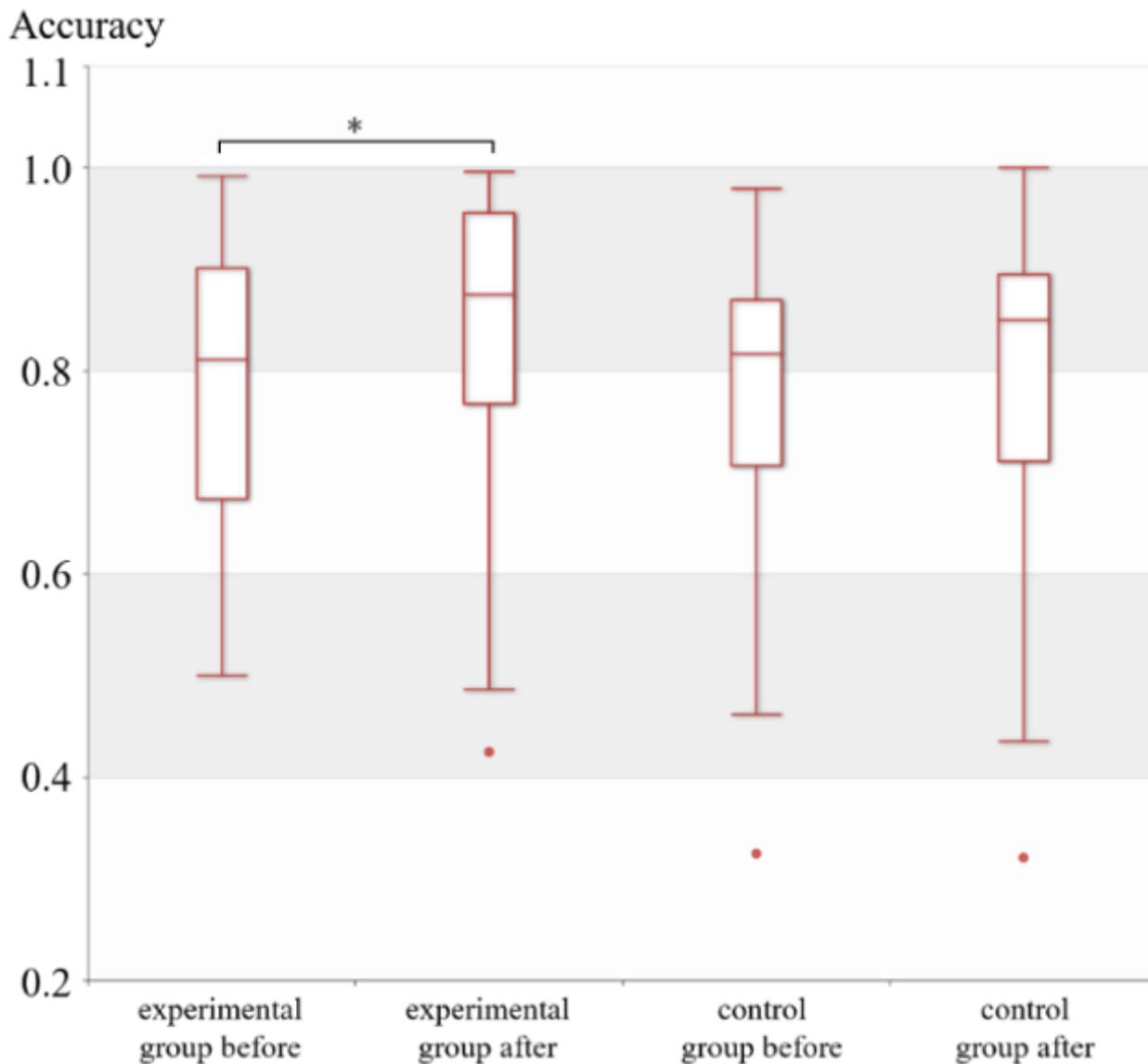
(a)



(b)

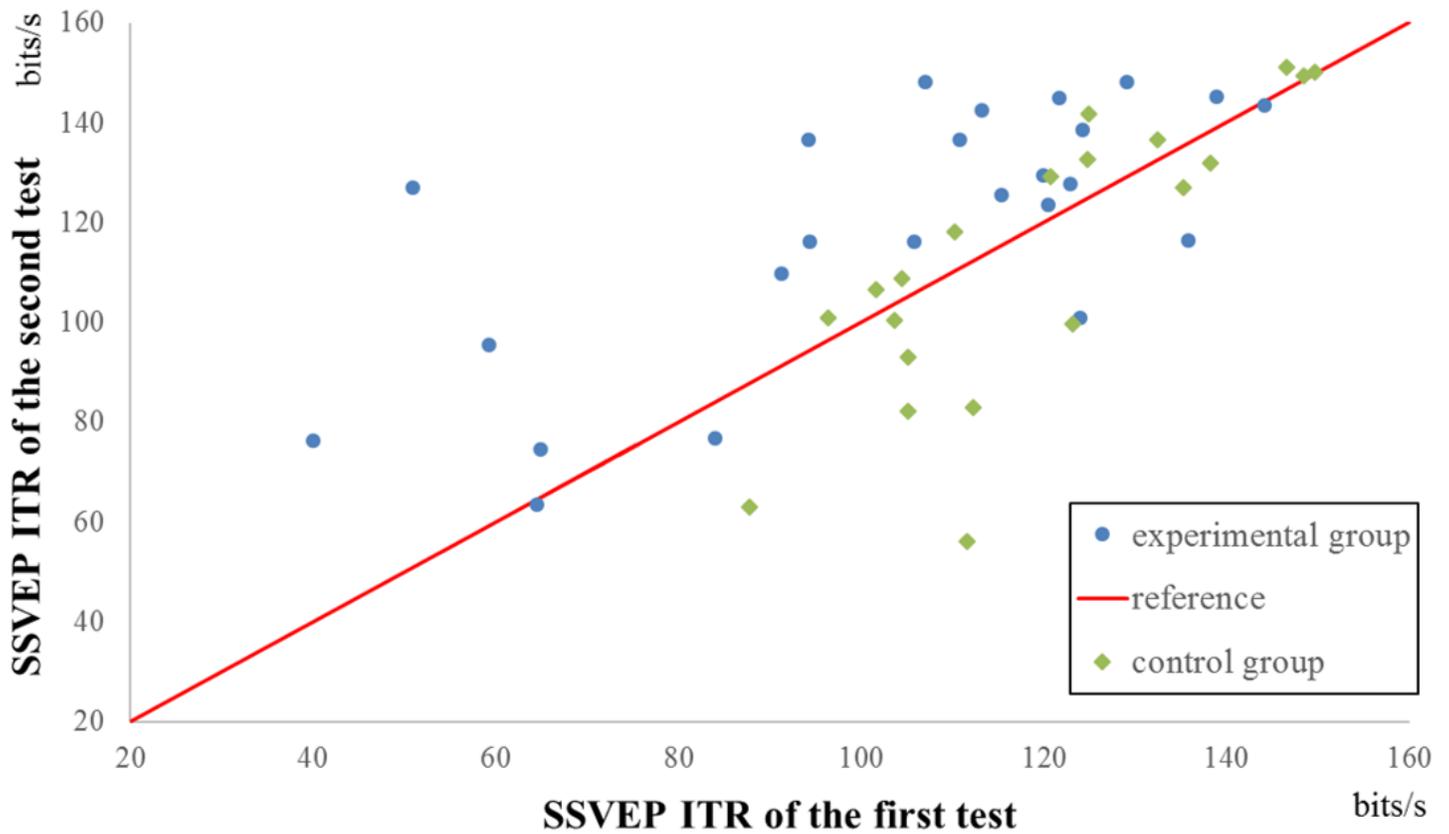
**Figure 8**

Neurofeedback training successfully improves the alpha-band power ratio in 22 of 24 subjects. (a) The figure shows that the training results of 24 subjects in the experimental group, in which 22 subjects shows improvement of various degree, and the two subjects whose alpha band power does not change a lot. It suggests that neurofeedback training is successful. (b) Statistically averaged alpha-band power ratio and variance are shown in the figure, and it can be seen that the statistical results have significant differences between before and after training. (Error bar indicates the SD, \* represents the significant difference,  $p < 0.05$ ).



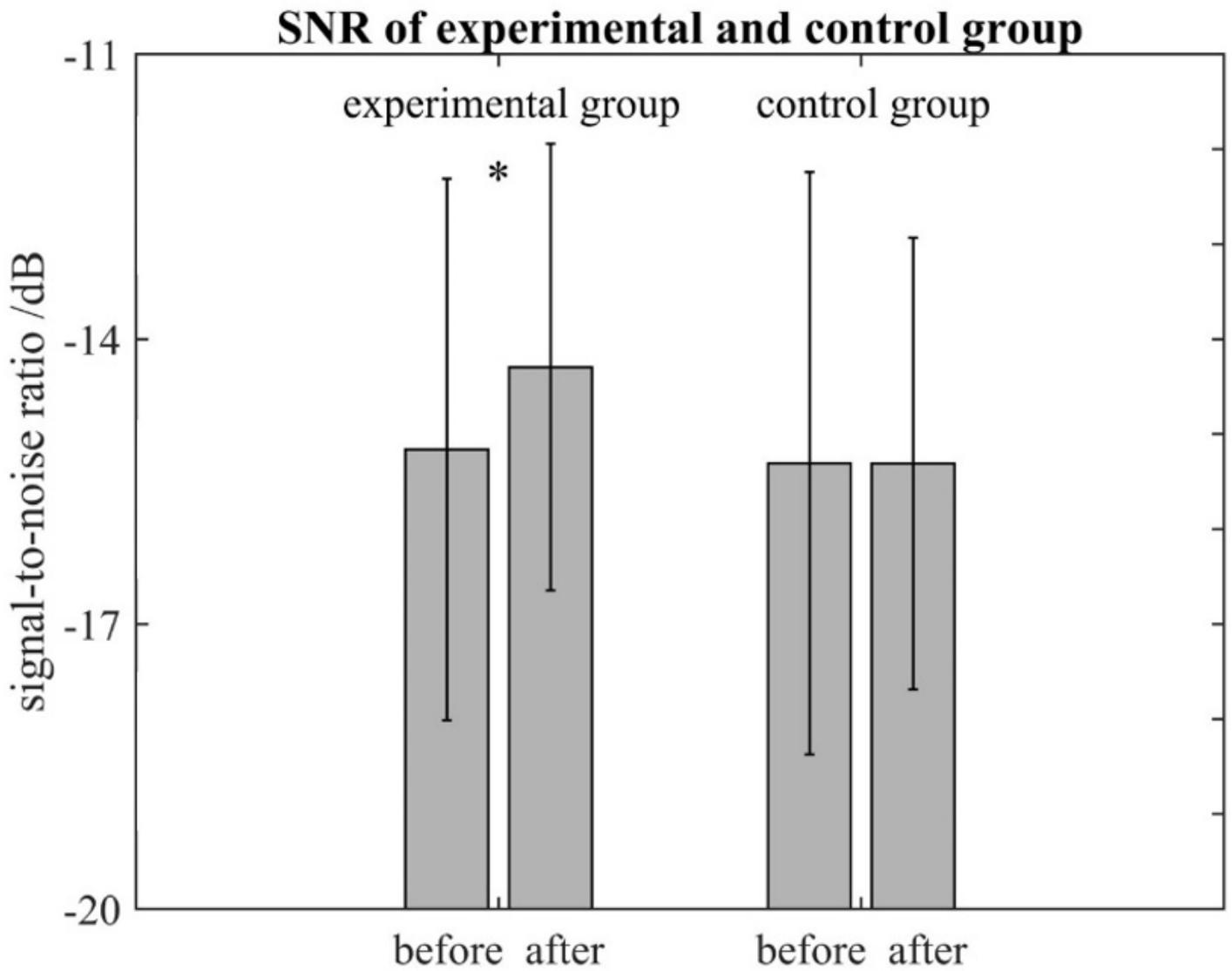
**Figure 9**

SSVEP-based BCI accuracy is dramatically increased after neurofeedback training. The figure shows the distribution of the SSVEP-BCI accuracy. Box graph statistical recognition accuracy distribution makes it clear that training makes the classification accuracy improve dramatically. And there were significant differences in the results before and after training of the experimental group, but almost no differences in the control group. It can also be seen from the diagram that the distribution of the first test results of the experimental group is approximately the same as that of the control group, in which the singular points are not in the statistical range and have been marked. (Error bar indicates the SD, \* represents the significant difference,  $p < 0.05$ ).



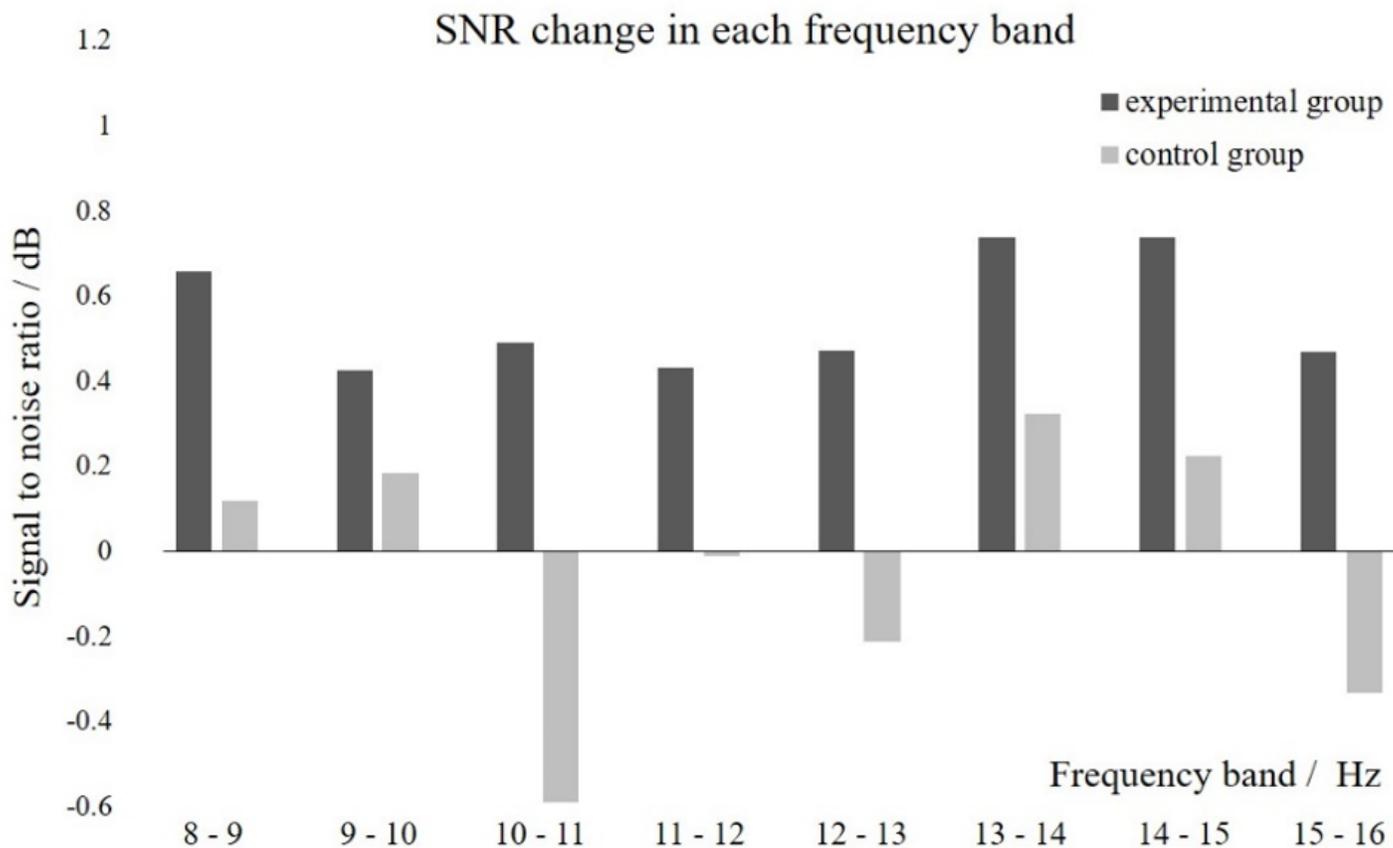
**Figure 10**

The NFT speeds ITR of the SSVEP system (50% chance of resampling to eliminate the singularity repeat for 100 times). The blue dots indicate the results of the experimental group and the green dots indicate the ITR of the control group. The red line is the reference line. The figure shows that most blue dots tend to be distributed in the upper left area, which means that the training results are better than that before training. While the green dots tend to remain at the same level, distributing around the red line.



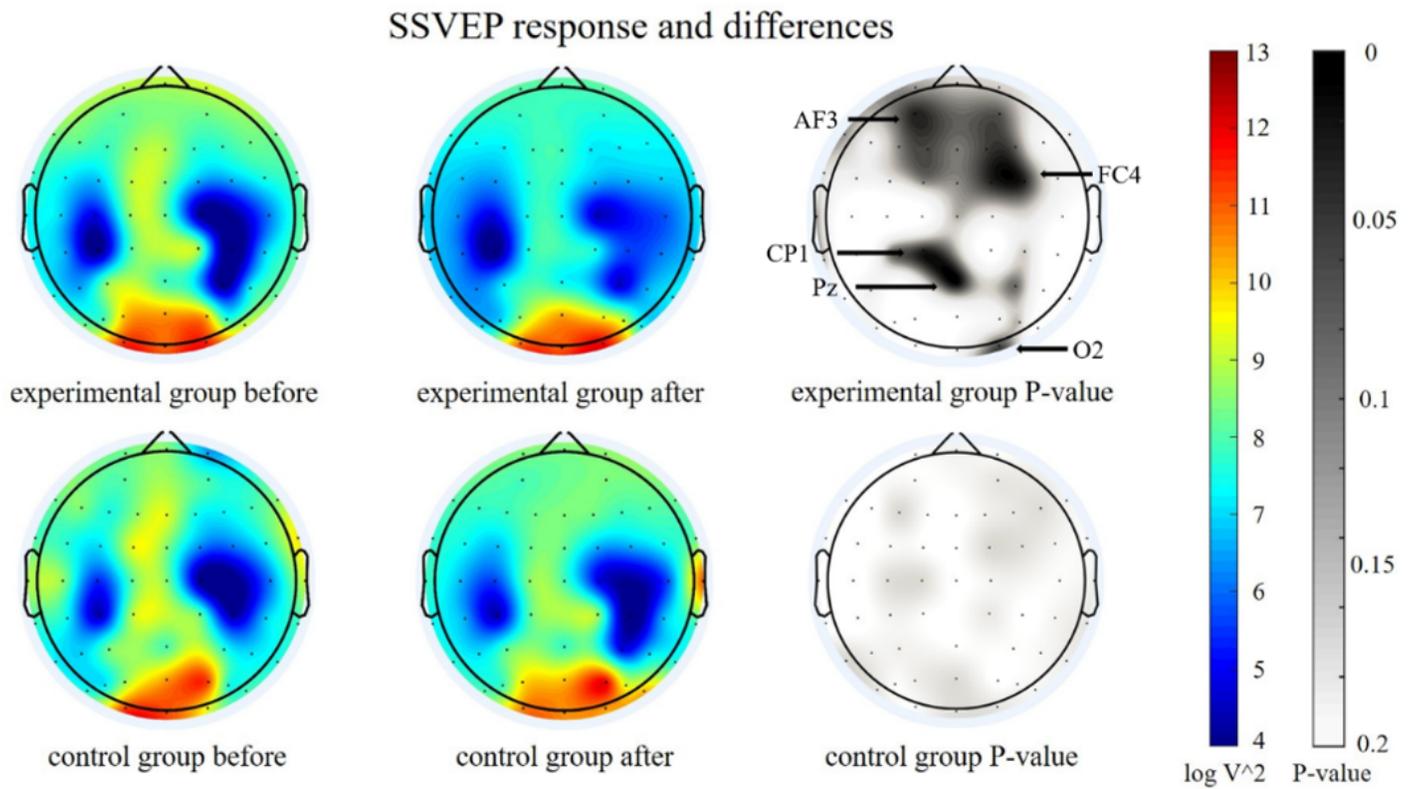
**Figure 11**

Statistical averaged SNR of SSVEP signal is considerably improved after NFT in the experimental group. It can be seen that the SNR of the first test of the training group and the test of the control group is not much different, while the second test of the experimental group showed a significant improvement in signal to noise ratio. This is a phenomenon not observed in the control group, excluded the possibility that the skilled use of the SSVEP-based BCI system is the main reason for the improvement of the experimental group. (Error bar indicates the SD, \* represents the significant difference,  $p < 0.05$ ).



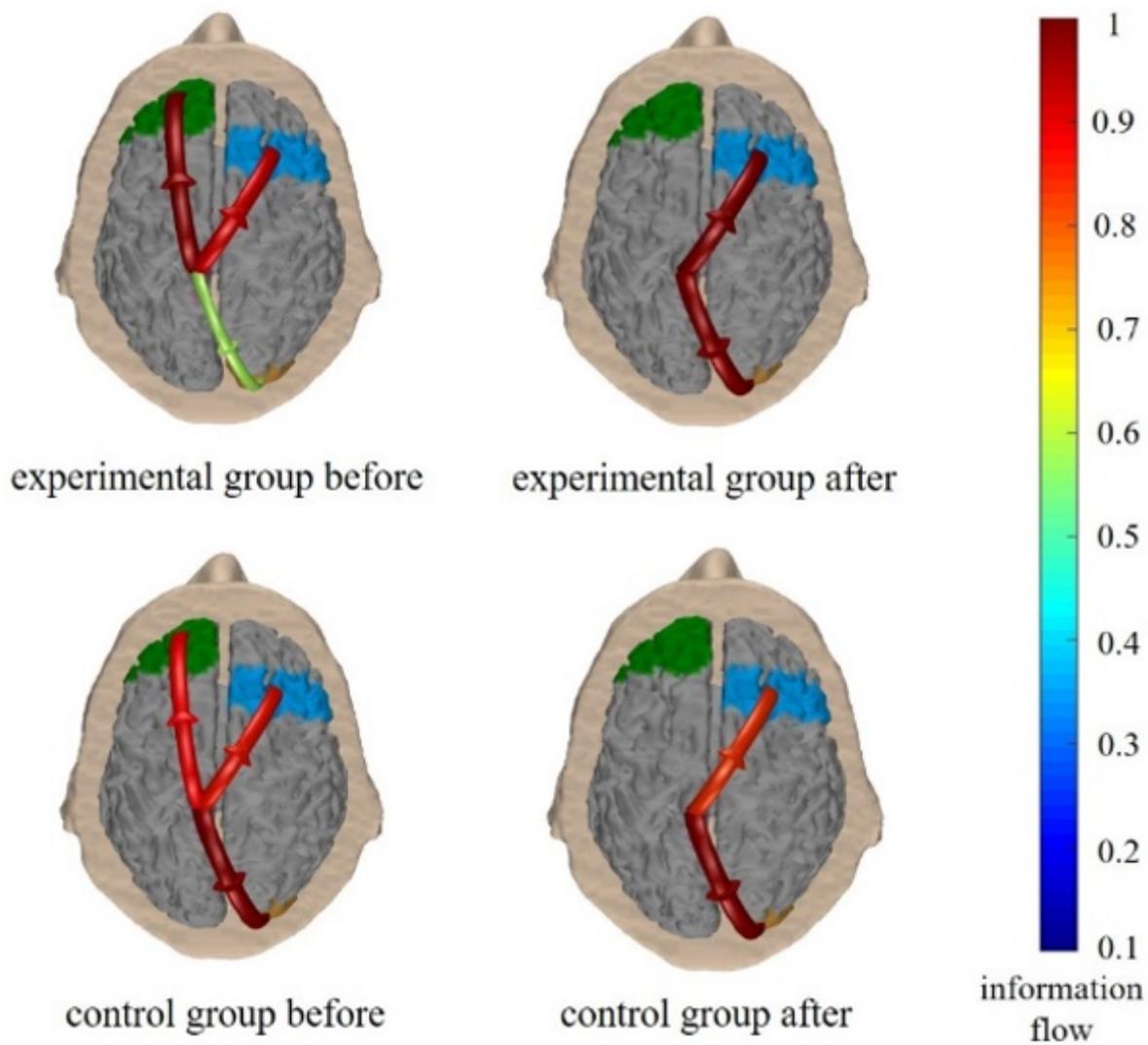
**Figure 12**

The figure shows the SNR changes in each frequency band of the experimental group and the control group. The experimental group had improved in each frequency band, while the change in the control group seems like randomly.



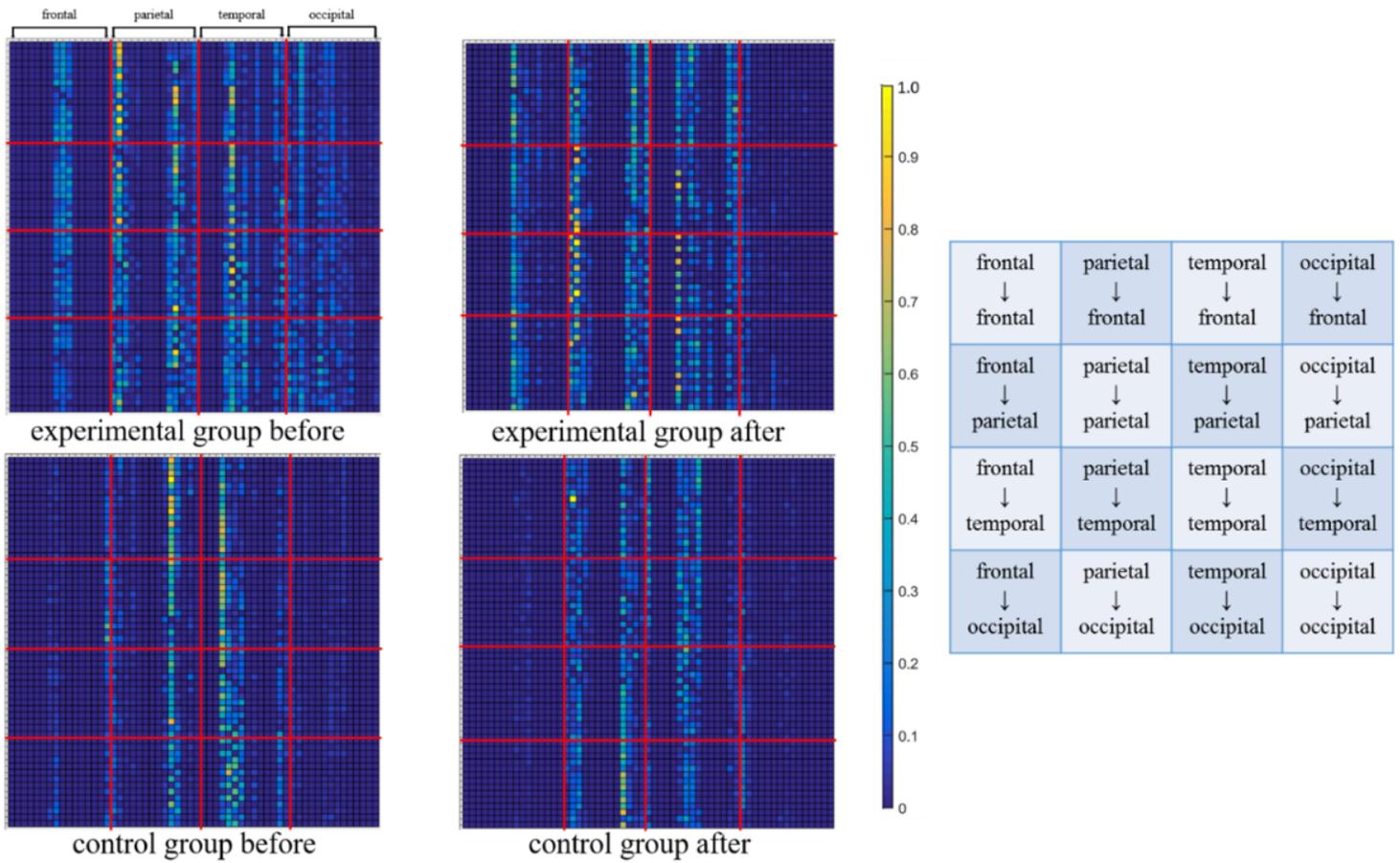
**Figure 13**

SSVEP frequency response and paired-sample t-test P-value statistical topographic map. The graphic color of the second data acquisition of the experimental group indicates that the training has achieved the purpose of reducing interference. For the experimental group, these are the locations that have differences ( $p < 0.1$ ): AF3, FC4, CP1, Pz, O2. Importantly, the O2 has a significant difference ( $p < 0.05$ ).



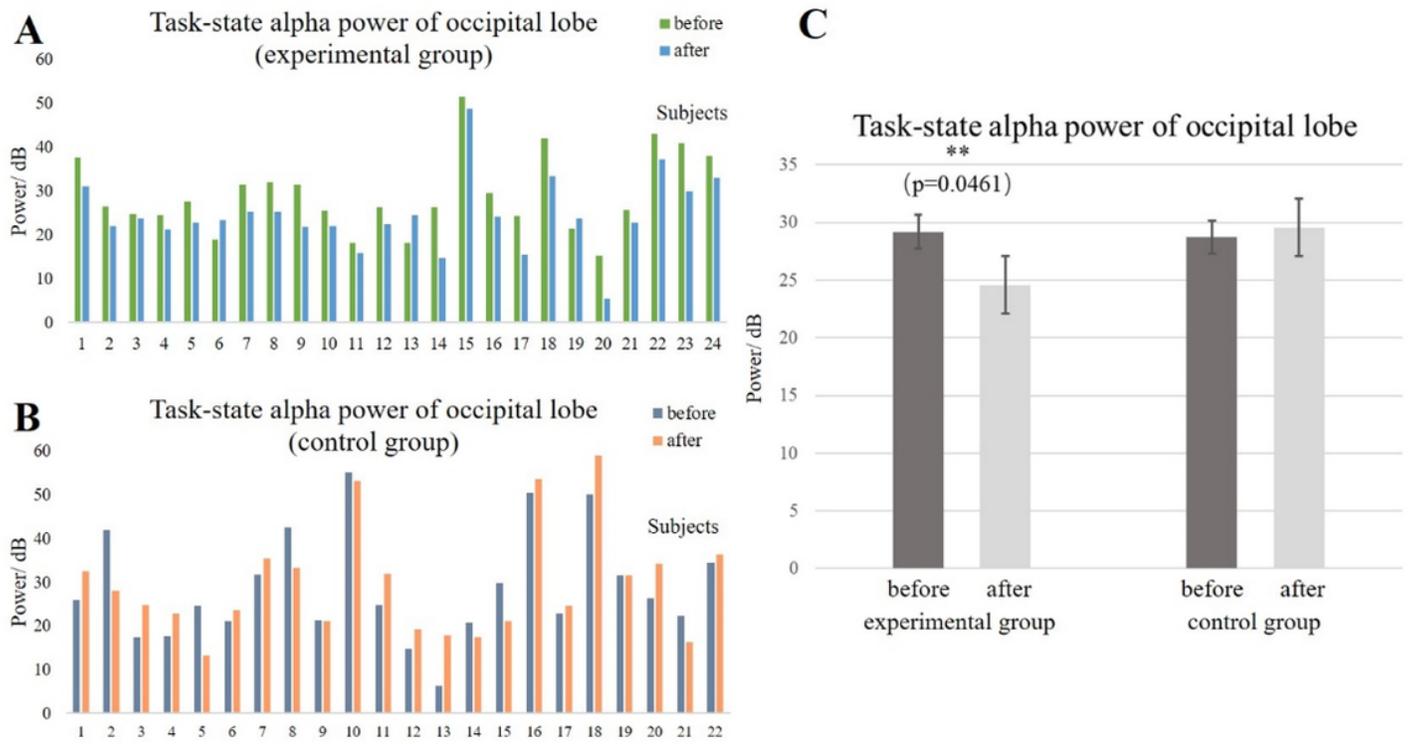
**Figure 14**

The figure shows the information flow of cortical functional connectivity in the SSVEP task among the right parietal lobe, occipital region, and frontal lobe. The information flow calculated using the directed transfer function (DTF).



**Figure 15**

The picture shows the detailed brain information flow of two groups of subjects in the SSVEP-based task state. The grid elements of the Matrix are 59\*59 electrode leads, and the subareas have been marked. The flow of information in the graph is from the row to the column. It can be seen that almost all the main hubs in the network have the flow of information to the whole brain, while the unimportant nodes have little information exchange.



**Figure 16**

The picture shows the background alpha component (task-state) of the occipital lobe. In figure A, the alpha power of the experimental group in the occipital lobe decreased significantly, and the results passed the paired-sample t-test ( $t=23$ ,  $p=0.0461$ ). In figure B, the alpha power of the control group in the occipital lobe shows no statistical regularity. And the average and variance value of two groups before and after the experiment is given in figure C.