Thesis Proposal: Alpha Down-Regulation Neurofeedback Training Effects on SSVEP-Based BCI Performances

by

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Abstract

Brain Computer Interface (BCI) is a system that provides their users with communication channels to control computers or devices. BCI systems have been primarily developed based on three BCI paradigms: motor-imagery (MI), event-related potential (ERP), and steady-state visually evoked potential (SSVEP) [1]. Among all BCI paradigms, SSVEP possesses high ITR and needs little training. A recent benchmark had achieved an average classification accuracy and ITR of 93% and 307 bit/min respectively using SSVEP-BCI with stimulus frequency from 8 to 15.8Hz, which is significantly higher than the current state-of-the-art BCI speller [2].

One biggest problem of BCI is the 'BCI-illiteracy' or 'BCI-incompatibility' phenomenon [3], referring the non-negligible portion of participants who were incapable of utilizing a BCI due to their low performances. For instance, Lee reported the rate of low performances in SSVEP were 10.2% while for MI and ERP, it was 53.7% and 11.1% separately [1]. Strategic approaches proposed to elicit the BCI performances were investigated in many studies. The majority of recent approaches can be grouped into: hardware and setup [4-7]; system design and protocol [8-13]; signal processing and classification algorithms [7, 14, 15].

Besides strategic approaches, neurofeedback (NF) training has been applied as an approach to voluntarily strength the elicited EEG patterns or enhance various types of BCI performance. Through a clearly understandable and instantaneous feedback in the form of spectral power, event-related potentials or slow cortical potentials, participants are supposed to find and adapt strategies to purposefully alter their brain states in accordance with prior instructions [16, 17]. Through multiple sessions, real impact on the user's behavior can be achieved.

This thesis plans to contribute the enhancement of SSVEP based BCI in a wide frequency range via NF training. The first contribution is that it proved that IAB down-regulation NF could benefit low-frequency SSVEP-BCI performances for non-selected subjects. Moreover, it further investigated whether NF training could also benefit the SSVEP-BCI with higher-frequency stimulus. In addition, the brain connectivity network was investigated during NF training, which could help explain the NF mechanism and therefore, contribute to more effective SSVEP-based BCI applications.

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Chapter 1: Introduction of EEG and Neurofeedback

1.1. Introduction of electroencephalograph (EEG)

Electroencephalograph (EEG) is an invasive technique to detect and record summed voltages brought by cortex activities on scalp. Different from invasive approaches which inserts electrodes or disables brain parts for behavior observation, EEG could be applied on human beings without ethical considerations. Unlike medical filming techniques, EEG recording has high temporal resolution thus largely applied on detecting event-related potentials which lasts only a few milliseconds.

EEG signals are usually described with different features such as voltage amplitude, scalp area, spectrum, latency, and so on. In fact, what the EEG cap records is the potential difference between the active electrode on scalp and the reference electrode. In order to get the exact values of these parameters, we need to use the least active electrode points as a reference to measure the most ideal raw data. Therefore, setting the reference electrode in the scalp recording measurement is of significant impact on EEG recordings. Various researches have investigated the chosen reference electrode and its effects on their results. Besides, Yao proposed reference electrode standardization technique (REST) to standardize a reference of scalp EEG recordings to a point at infinity [18]. Recently, Tian and Yao demonstrated if mixed neural potentials vary with experimental conditions, then the reference values for each experimental condition would not be fixed, thus distorting the true amplitude difference between different experimental conditions [19]. Yet no uniformed standards were found for reference selection in different applications. Liang presented [20]:

(1) If the original EEG amplitudes have the same trend of change as their respective reference values, the amplitude difference will be weakened;

(2) If the reference values have opposite trends as the original EEG amplitudes, their respective their amplitude differences will be increased;

(3) When the original EEG amplitudes of the two conditions are the same, the difference in amplitude between them will depend entirely on their respective reference values.

EEG recording is conventionally obtained by placing electrodes on scalp with a conductive gel. Before smearing the gel, light abrasion on scalp area as well as ground and reference channel by scrub paste was performed to reduce the impedance due to dead skin cells, thus lower the impedance between electrodes and scalp.

At present, multi-channel EEG equipment is mostly used in medical and scientific research fields. At the same time, in the field of EEG research or application scenarios, multi-channel EEG equipment generally uses wet electrodes, but the preparation before experiment could be complicated and cumbersome. And these steps would make EEG researches or applications to be time-consuming and labor-intensive. In recent years, dry EEG Electrodes were invented, and wireless EEG systems were put into application. Compared with wet electrode EEG devices, dry electrode devices are much more convenient to use, eliminating the need for washing the head or applying conductive paste, etc. However, rare studies could prove the signal recorded from dry electrode devices overwhelms the conventional wet EEG electrodes. Indeed, the collection of the EEG signal by the dry electrode is disturbed and skin capacitance is a major factor that interferes with the instability of dry electrode EEG devices.

In most EEG recordings, a common system reference electrode is connected to one input of a differential amplifier (one amplifier per pair of electrodes) while a ground electrode is connected to the other input of each differential amplifier. The active electrodes on EEG scalp usually follows the 10-20 International System, as shown in Figure 1-1.

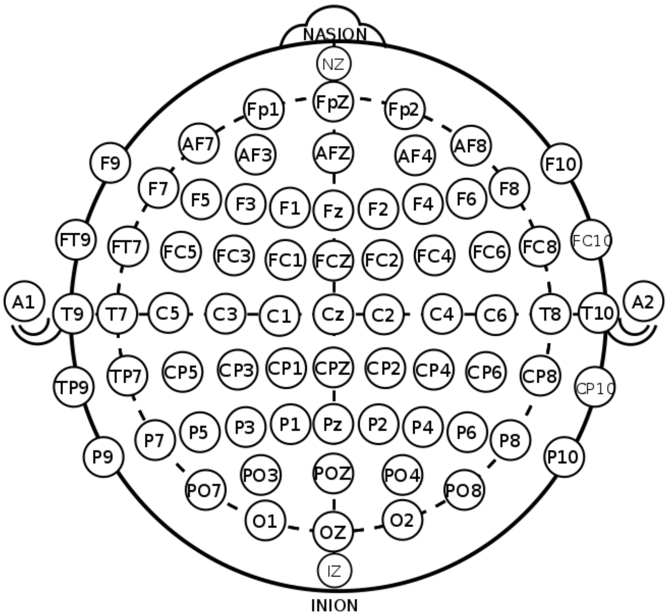

Figure 1-1 International 10-20 system for EEG electrode placement, showing modified combinatorial nomenclature.

These amplifiers will amplify the voltage between the active electrode and the reference electrode. In analog EEG, the signal is then filtered. However, most EEG systems in recent years are digital, and right after being filtered by an anti-aliasing filter, the amplified signal is always digitized via an analog-to-digital converter.

Table 1-1 Devices & parameters, for cognitive science applications

Company	NeuroScan	EGI	Brain Products	Symtop
Device	SynAmps 2	NetAmps 300	DC	UEA
Common mode rejection ratio	110 dB	120 dB	120 dB	98 dB
Bandwidth	DC-3500 Hz	DC-4000 Hz	DC-4000 Hz	0.5-120 Hz
Sampling rate	20,000 Hz	20,000 Hz	1000 Hz	1000 Hz
A/D digits	24	24	16	16

The latest EEG recording products for cognitive science or clinical diagnosis are listed in the above table (Table 1-1). The first three devices are of high precision that can support the EEG investigation in cognitive science while the last device is only enough for clinical diagnosis.

1.2. EEG Frequency Bands

Rhythmic activity, described in frequency domain, was a common measure of EEG signal, and dominant cerebral signal in the scalp falls in the range of 1–20 Hz. EEG are subdivided into bandwidths commonly defined as Alpha (8 -12 Hz), Delta (0.5 - 4 Hz), Theta (4 - 8 Hz), Beta (15 - 30 Hz), and Gamma (30 -100 Hz).

Alpha is frequency of neural oscillation ranging from 8 Hz to 12 Hz named after Hans Berger named as the first rhythmic EEG activity. This was the "posterior basic rhythm", because it appears in the posterior regions of the head on both sides, higher in amplitude on the dominant side. When a subject is in awake and eye-closed resting state, alpha wave power will be enhanced. On the contrary, when the subject is blinking, eyes-open, or in mental exertion, alpha wave power will be weakened. This electrophysiological phenomenon is called a suppression or desynchronization. If the subject backs to in quiet eye-closed state again, the alpha wave will reappear and be enhanced again.

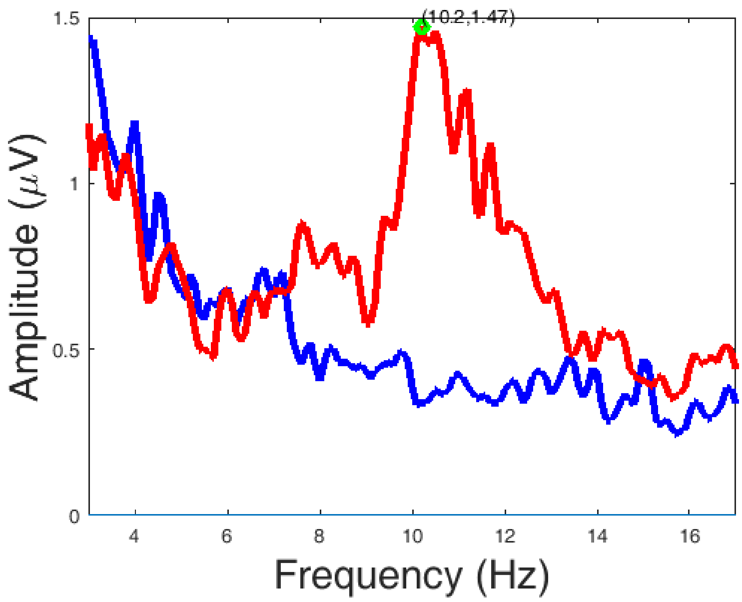

Figure 1-2 An example of the resting baseline using moving average. Eye-open signal is plotted in blue line and eye-closed signal is plotted in red line.

Individual alpha frequency is defined in terms of peak within the traditional alpha frequency range about 7.5-12.5 Hz. Peak alpha frequency (PAF) is that spectral component which shows the largest power estimate, and it has inter-individual difference. Take the signal of frequency domain in Figure 1-2 as an example, the PAF for this subject is 10.2 Hz. In this study, the training parameter of NFT was the relative individual alpha band (IAB) amplitude at channel Oz. Individual alpha peak frequency (IAPF) was calculated as the peak frequency of the alpha band during the initial resting eye-closed baseline session. Thus, the relative individual calculated by the following equation:

$$\text{Relative IAB amplitude} = \frac{\sum_{k=LTF/\Delta f}^{HTF/\Delta f} X(k)}{HTF - LTF} \Big/ \frac{\sum_{k=0.5/\Delta f}^{30/\Delta f} X(k)}{30 - 0.5}$$

where LTF denote the low transition frequency from IAPF-4 Hz to IAPF Hz, and HTF denote the high transition frequency from IAPF Hz to IAPF+2 Hz.

Besides the alpha band, activities of other frequency bands have also been demonstrated to be related with different behaviors or states and differs in ages, diseases, etc. Specifically, Delta is a high amplitude but slow speed wave that related to the slow-wave sleep (SMS). Theta relates to sub-consciousness and can be enhanced in deep sleep and deep meditation. Beta activity has close link with motor behavior, and it attenuates during active movements. And Gamma waves is likely to have some relationships with the creation conscious unit.

1.3. Neurofeedback

1.3.1. Introduction of Neurofeedback (NF)

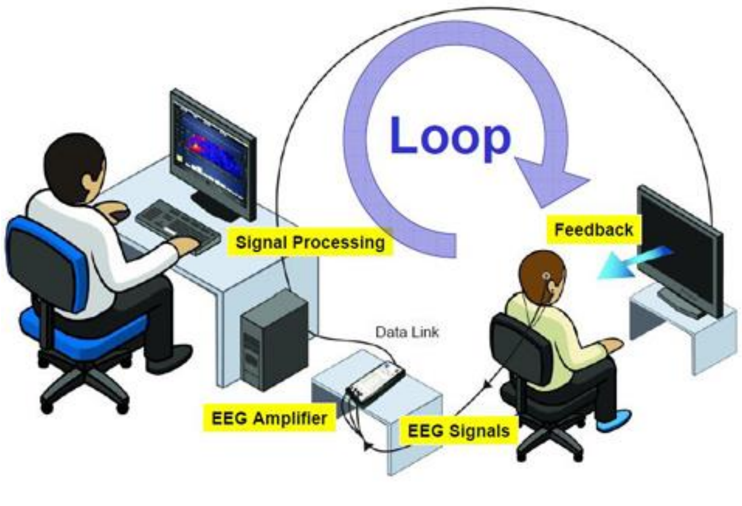

Figure 1-3 The paradigm of NF training with visual feedback

NF training has been applied as a bio-training approach to voluntarily strength the elicited EEG patterns or enhance various types of BCI performance, and to build a joint between rhythmic cortical activities and electrical devices such as computer. Through a clearly understandable and instantaneous feedback in the form of spectral power or functional connectivity, participants are supposed to find and adapt strategies to purposefully alter their brain states in accordance with prior instructions [16, 17]. Through multiple sessions, real impact on the user's behavior can be achieved. As the training went by, the threshold of visual reward would fit to the amplitude of alpha band measured previous session, therefore, their brain will have to keep on thinking workable mental strategies to get rewarded. In this study, we use NF to reduce activities of alpha waves through visual reinforcement.

Milestones in NF development was summarized. Berger first proposed the concept of EEG and defined the different frequencies of brain waves in 1929. A series of long-term studies by Sterman in 1996 have shown that both cats and humans learn to increase the amplitude of the 12-15 Hz frequency range in the sensorimotor cortex. In addition, they have found that patients with grasping disorders can increase the sensory motor rhythm SMR by operational conditioning. Lubar first applied EEG biofeedback therapy to patients with ADHD. Their training in ADHD children mainly involved the enhancement of brain SMR rhythm.

1.3.2. Synchronization and desynchronization

For the same training EEG band, it could have two training direction: synchronization and desynchronization. For instance, the enhancement of upper alpha neurofeedback training improves working memory performance and SMR desynchronization in motor tasks [21, 22] whereas decrease of alpha activity by NF has benefits on low frequency SSVEP BCI performances [23]. In this study, the synchronization and desynchronization were also named as up-regulation and down-regulation separately.

1.3.3. Alpha Down-regulation NF Training

Only a few studies have investigated the Alpha down-regulation NF. For instance, Ros reported the alpha down-regulation could benefit the therapies of brain disorders as well as reduction of mind-wandering and may engender better cognitive performance, such as a faster response [24]. Besides, he also demonstrated a short time NF training, i.e. one single session of this NF, could encourage the early acquisition of a procedural perceptual-motor task.

1.3.4. Specific or non-specific NF effects

The effects of spectral NF training on EEG bands other than the training band has reported to be different in various researches. Zoefel found the upper IAB amplitude changes in NF training was independent of other frequency spectra [17]. Kober summarized prior studies report SMR-NF changes only in the trained EEG spectra while he found SMR-based NF training led to unspecific changes in delta and alpha power as well. Besides, gamma training affected nearly the whole power spectrum [25]. Jurewicz reported beta up-regulation NF was accompanied by alpha power increase. Nevertheless, rare studies reported the IAB down-regulation NF effects on other EEG spectra [26].

Chapter 2: Introduction of Brain-Computer Interface and Approaches to Enhance Its Performance

2.1. Overview of Brain-Computer Interface (BCI)

Brain Computer Interface (BCI) is a system that provides a direct connection between the human brain and a computer or other electronic device. BCI systems have been primarily developed based on three BCI paradigms: motor-imagery (MI), event-related potential (ERP), and steady-state visually evoked potential (SSVEP) [1]. Among all BCI paradigms, SSVEP possesses high ITR and needs little training.

MI signal is elicited when people are imaging or going to do unilateral movements, e.g. left and right hands, while the hands do not actually move. During MI, the energy in the sensory region of the contralateral side of the brain will be reduced, and the μ (8-12 Hz) and β rhythm (13-30 Hz) in ipsilateral motor sensation zone will increase in power as a result of mutual weakening (Event-Related Desynchronization, ERD) and enhancement of post-synaptic potentials (Event-Related Synchronization, ERS) in brain neurons. By recording the brain's brain signals and extracting features, the brain's thought activity is inferred and translated into corresponding commands to control external devices or computer.

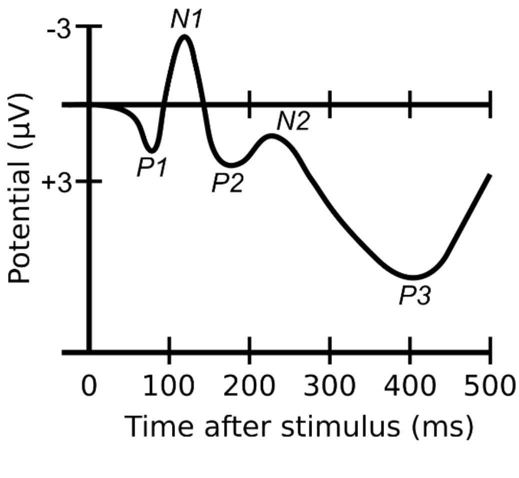

Figure 2-1 A waveform showing ERP components

Event-related potentials are a kind of signal mode that is of great concern in the research of brain-computer interface system based on EEG. The main components of the classic ERP include P1, N1, P2, N2, and P3, as shown in Figure 2-1. The first three are called exogenous components, and the latter two are called endogenous components, which are closely related to cognitive processes. According to the different stimulation modes, it can be divided into single sensory channel stimulation induced by visual, auditory and somatosensory. Compared with the single sensory channel, the event-related potential induced by trans-sensory channel stimulation would be of high amplitude, short latency and high-dimensional spatial distribution information, compensating for the defects of too little and unfavorable identification of single sensory-evident events. Therefore, the faster information conversion speed and higher classification accuracy rate makes ERP of higher practical value in the BCI.

SSVEP is evoked by external stimulus as the retina receives a visual stimulus from 3.5 Hz to 75 Hz, the brain produces electrical activity at the same frequency or harmonic frequencies of the visual stimulus. After the human brain signal of the flash stimulation is amplified and A/D converted, the EEG signal is processed, the frequency value of the energy is analyzed, and compared with the flashing frequency of the flash stimulator, the corresponding action is determined. Finally, a control signal is sent to the external control device or computers.

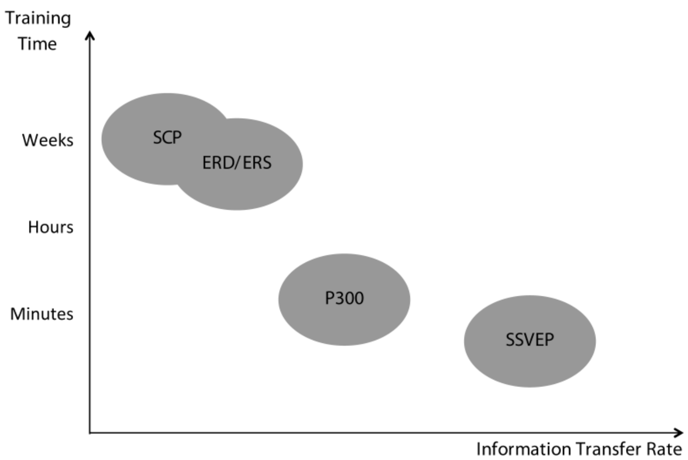

Figure 2-2 General comparison of slow cortical potential (SCP), ERD/ERS, P300, and SSVEP with respect to their training time and information transfer rate.

Among all BCI paradigms, SSVEP possesses high ITR and needs little training, as indicated in Figure 2-2 [27]. A recent benchmark achieved an average classification accuracy and ITR of 93% and 307 bit/min respectively using SSVEP-BCI with stimulus frequency from 8 to 15.8Hz, which is significantly higher than the current state-of-the-art BCI speller [2].

2.2. BCI-illiteracy and Approaches for Enhancing BCI

One biggest problem of BCI is the ‘BCI-illiteracy’ or ‘BCI-incompatibility’ phenomenon [3], referring the non-negligible portion of participants who were incapable of utilizing a BCI due to their low performances. For instance, Lee reported the rate of low performances in SSVEP were 10.2% while for MI and ERP, it was 53.7% and 11.1% separately [1]. Strategic approaches proposed to elicit the BCI performances were investigated in many studies. The majority of recent approaches can be grouped into: hardware and setup [4-7]; system design and protocol [8-13]; signal processing and classification algorithms [7, 14, 15].

For BCI protocol, the stimulus type, color and timing are reported to be relevant for an efficient performance and related with the illiteracy in P300 BCI [6]. In SSVEP-BCI, the layout of the speller would have significant influence on the speed of BCI operation [7].

Both multi-modal hybrid and brain activation pattern hybrid have been studied to improve BCI classification accuracy and avoid certain type of illiterate. The hybrid of ASSR and P300 BCI is presented to outperform the sole ASSR or P300 BCI system [11].

Chabuda found the shape of the response pattern of subjects who could perform the task via 7-letter SSVEP-speller can be distinct from those subjects who could not and estimated the difference by AUC for distribution of correlations of temporal patterns and for distribution of SNRs [7]. In another research, novel algorithms were proposed based on SSVEP features enhance the BCI system stability (online) and achieve better classification performance (offline) [14].

In recent years, neurofeedback has been applied as an alternative approach to enhance the performance of various type of BCI application. Basically, it works in two ways 1. wherein the desired patterns of the brain activities are rewarded by visual or auditory stimuli that depend on the online feedback of the relevant components in the EEG recorded from one or more electrodes placed on the scalp during NFT (Vernon 2005); or 2. using neurofeedback training (NFT) to strengthen the elicited electroencephalogram (EEG) patterns. NFT refers to an operant conditioning paradigm that helps subjects to voluntarily modulate their brain electrical activities. hypothesis of NFT is that through real-time feedback of brain activity, the user learns to self-regulate his or her own brain function in order to improve certain behavior or cognitive performance. Numerous studies have demonstrated positive effects of NFT on enhancement of human cognitive and behavioral performance [16, 24, 28-30] as well as in treatment of mental disorders such as attention-deficit/hyperactivity disorder (ADHD), autistic spectrum disorder, and major depressive disorder.

2.3. Predictors of SSVEP-BCI Performance

Voluntary factors in resting state has been investigated to make predictions on SSVEP-BCI performances, avoiding frustrated feelings and improving SSVEP-BCI efficacy. Zhang found classification accuracy of SSVEP-BCI under five stimulus frequencies (7.05, 10, 12, 15 and 20 Hz) could be predicted by (or close to significant with) the resting state functional connectivity of the corresponding frequency coherence as well as the three averaged network measures (mean functional connectivity, clustering coefficient, and characteristic path length) [31]. In addition, researchers found the resting alpha amplitude negatively correlated with low frequency SSVEP-BCI classification accuracy [23, 32]. However, it seemed not the same case for higher frequency SSVEP. Won presented the resting alpha amplitude was not correlated to classification accuracy of higher frequency SSVEP-BCI [32]. Considering higher frequency SSVEP plays an important role in SSVEP-BCI as it has less artifacts and can cause much less visual fatigue [33], it was in demand to further investigate the relation between resting EEG spectra and higher-frequency SSVEP-BCI.

Chapter 3: Experiment Methods

3.1. Participants

A total of 28 healthy adults (age, 25.1 ± 3.2 years; 7 females) with normal or corrected to normal vision and no self-reported chronic medication/substance intake/neurological diseases such as epilepsy, participated in this study. Participants went through a two-day IAB down-regulation NF training. Before and after NF training, SSVEP tests were performed. In order to reduce visual fatigue and control experiment time, participants were randomly allocated to 2 groups in SSVEP tasks with different stimulus frequencies. Other parts of the experiment protocol were consistent in two groups. All participants signed an informed consent form after the experimental nature and procedure were explained to them. The experimental protocol was in accordance with the Declaration of Helsinki and approved by the local research ethics committee (University of Macau).

3.2. EEG Recordings

The data were recorded in our lab experiments and the hardware settings were consistent with our previous study [23]. EEG signals were collected from standard Ag-AgCl electrodes placed on the scalp according to the international 10–20 system. The ground was located at the forehead and the reference was selected as the left mastoid. The impedance for all electrodes was kept below 10 kΩ. The signals were amplified through an amplifier (g.USBamp, Guger Technologies, Graz, Austria) with a sampling rate of 600 Hz in SSVEP-based BCI test, and 256 Hz in the baseline recording and the NFT part. In avoid of eye fatigue that might cause tears and blinks, the SSVEP stimuli was presented in a low contrast and brightness screen.

An online bandpass filter between 0.5 Hz and 60 Hz and a 50 Hz notch filter were enabled in the amplifier to filter the higher frequency noise, baseline drift and power line. In offline analysis of baseline, NF training and SSVEP signals, Butterworth bandpass filter between 0.5 Hz and 40 Hz was applied and for those data points with absolute amplitude exceeding 75 μV were regarded as noise and removed in time domain. The SSVEP signal of one participant (the subject 12) in Group A was contaminated and thus excluded in the SSVEP-related data analysis in this study.

3.3. Experimental design

3.3.1. Experimental procedure

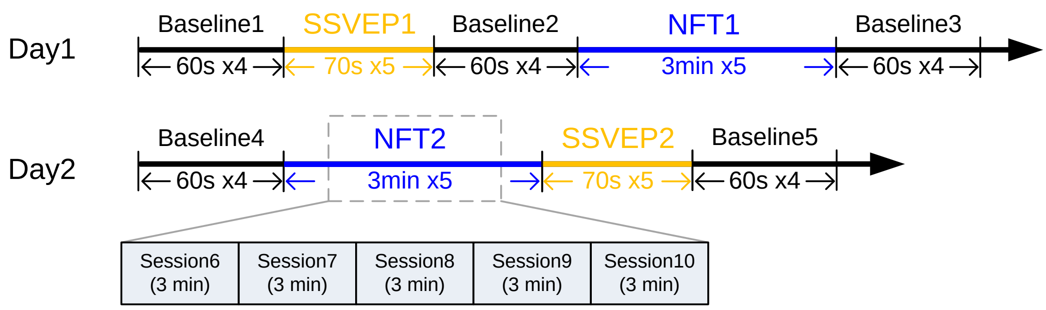

Figure 3-1 Experimental procedure

Participants were instructed to follow the training protocol and attempted to decrease their individual alpha amplitude via trials of mental strategies over 10 training sessions. The main objective of this study is to apply NF training to investigate its effects on a broad range (7.05-35 Hz) of SSVEP- based BCI performance evaluated by BCI classification accuracy and SSVEP SNR. 28 non-selected participants were equally and randomly allocated to a low stimulus frequency SSVEP group (age: 25.5 ± 3.6 years, 4 females) and a high stimulus frequency SSVEP group (age: 24.1± 2.6 years, 5 females). The experiment protocol is as shown in Figure 3-1. Participants completed the NFT in two consecutive days. Baseline recordings were performed before the initial SSVEP test (SSVEP1) and NF training sessions (NFT1 & NFT2). Participants in Group A and Group B went through experiment with the same arrangement, however, with different stimulus frequency ranges in SSVEP tests.

3.3.2. NF training protocol

The training parameter of NFT was the relative individual alpha band (IAB) amplitude at channel Oz. Individual alpha peak frequency (IAPF) was calculated as the peak frequency of the alpha band during the initial resting eye-closed baseline session. Thus, the relative individual calculated by the following equation：

$$\text{Relative IAB amplitude} = \frac{\sum_{k=LTF/\Delta f}^{HTF/\Delta f} X(k)}{HTF - LTF} / \frac{\sum_{k=0.5/\Delta f}^{30/\Delta f} X(k)}{30 - 0.5}$$

where LTF denote the low transition frequency from IAPF-4 Hz to IAPF Hz, and HTF denote the high transition frequency from IAPF Hz to IAPF+2 Hz.

Participants performed 5 NFT sessions each day in two consecutive days for a total of 10 training sessions, attempting to decrease their individual alpha amplitude. Each NFT session consisted of 3 successive 1-min trials with a 5-s interval between trials.

3.3.3. SSVEP stimuli

In SSVEP test parts, ten stimulus frequencies were selected as the visual stimuli for participants:

in Group A= {7.05, 7.50, 8.0, 8.57, 9.23, 10.00, 10.91, 12.00, 13.33, 15.00} Hz

in Group B= {17.00, 19.00, 21.00, 23.00, 25.00, 27.00, 29.00, 31.00, 33.00, 35.00} Hz

The SSVEP signals were recorded over the occipital cortex of the scalp (i.e., O1, O2, Oz, PO3, PO4 and POz). In total, 50 SSVEP trials were performed in 5 sessions. Each session consisted of 10 trials, and each trial used one stimulus frequency selected randomly and exclusively from the corresponding 10 stimulus frequencies in Group A and Group B. Moreover, each trial lasted for 7 s in which the stimulus was only flashing for 4 s and the remaining 3 s was for a short rest to prepare for the next trial. After each session, a break of 3 ∼ 5 min was given to the subject to relax. An LCD monitor was used as the visual stimulator (ViewSonic 22", 120 Hz refresh rate, 1680 × 1050-pixel resolution). A white stimulus with 120 × 120 pixels on black background was programmed with Microsoft Visual Studio 2010 and Microsoft DirectX SDK (June 2010). A '+' symbol was shown in the center of the flashing target to indicate the participants where they should focus their gaze.

3.4. SSVEP-BCI performance calculation

SSVEP signal SNR, defined as the ratio between the power of the stimulus frequency and the mean power of a 2 Hz frequency interval (i.e. n=4) centered on the stimulus frequency but excluding the stimulus frequency, which can be calculated as:

$$\mathrm{SNR} = \frac{n \times X(k)}{\sum_{k=1}^{n/2}[X(K+k) + X(K-k)}$$

where $K = f/\Delta f$ is the spectrum index corresponding to the stimulus frequency f, X(K) denotes the spectrum amplitude, and n is the number of the points in this spectrum interval (Wang et al 2006). In following analysis, the SSVEP signal SNR were computed as the mean SNR of corresponding ten frequencies and of participants in each group across six occipital electrodes.

3.5. Statistical analysis

Firstly, one-way ANOVA was applied to examine the differences of the training parameter, i.e. initial resting IAB, between two groups. Secondly, Pearson correlation test was employed to test the IAB change trend over ten NF training sessions. Additionally, paired-t test was used to examine the IAB differences between NF session 1 and NF session 10, which were right after the SSVEP1 and before SSVEP2, separately. On the other hand, in order to examine whether the IAB training influence other frequency bands, the change trend over ten NF session in other frequency bands, i.e. Sigma (12-16Hz), Beta1(16-20Hz), Beta2 (20-28 Hz), Delta (0.5-4 Hz) and Theta (4-8 Hz) bands, were also examine by Pearson correlation test. For SSVEP performances, group mean was calculated for signal SNR and classification accuracy, furthermore, paired-t test was performed between SSVEP tests.

Chapter 4: Preliminary Results of NF Training Effects on SSVEP-BCI Performance

4.1. Trainability of IAB

For each participant, the experiment consisted of 10 NF sessions within consecutive two training day the same week with 5 training sessions each day. Group mean relative amplitude of IAB were the following (Figure 4-1):

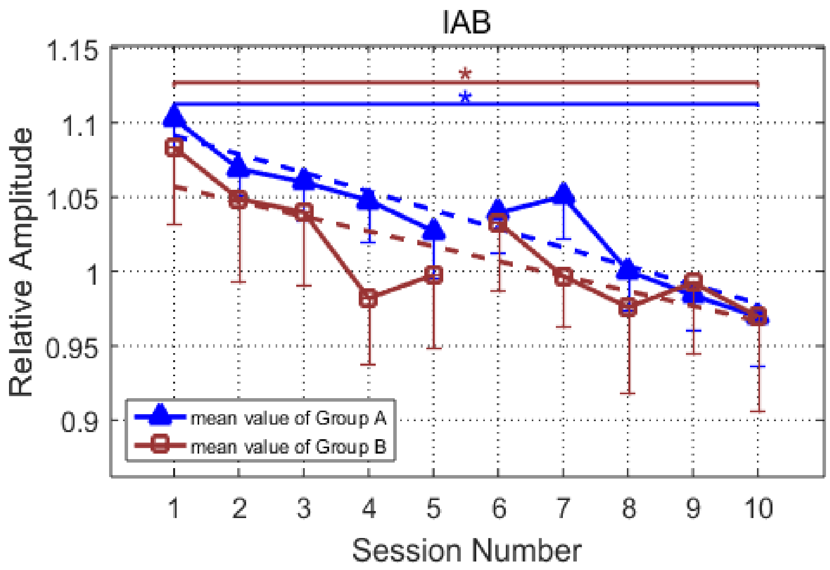

Figure 4-1 Mean relative amplitude of IAB (at channel Oz) in consecutive NF sessions. Dashed straight lines indicate significant correlation between session number and the mean amplitude of corresponding group. The bars indicate standard error of the mean, depicted one-tailed due to the directional trend of corresponding bands. The colored asterisks indicate significant differences between two NF01 and NF10 of corresponding group (*: p < 0.05).

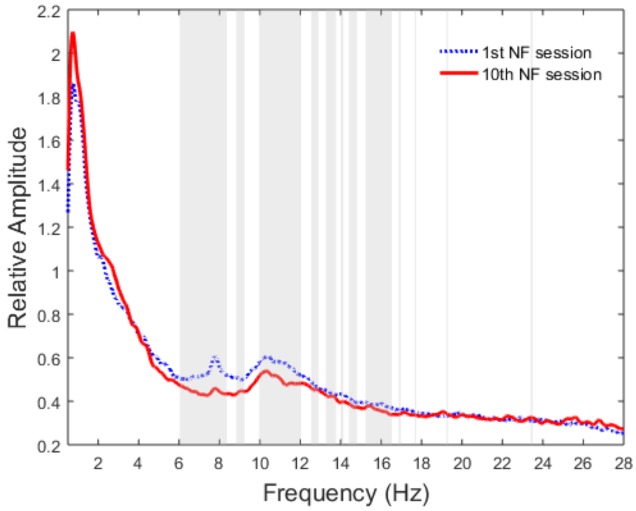

Figure 4-2 Mean relative amplitude of EEG frequencies (from 0.5 to 28 Hz, at Oz) in NF01 and NF10. Shaded area indicates continuously significant (p<0.01) suppression of corresponding frequencies in NF10 compared with NF01.

There was significant negative relationship between session number and the group mean relative IAB amplitude for both Group A (r=-0.933, p=0.0001) and Group B (-0.817, p= 0.0039), via Pearson correlation test. Paired-t test among sessions indicating the trainability of IAB down-regulation, based on the significance within certain training day and between NF10 and NF1. Both statistical analyses reflected the trainability of relative IAB amplitude in NF training.

4.2. EEG Frequency bands during NF

The mean relative amplitudes of Delta (0.5-4 Hz), Theta (4-8 Hz), sigma (12-16 Hz) and beta1 (16-20 Hz), beta2 (20-28 Hz) at Oz over 10 training sessions were depicted in Figure 4-3. Two-tailed Pearson correlation test was applied and those changes across sessions with significance were indicated as dashed straight line. Paired-t test further applied between NF10 & NF01 on 28 participants, and those sessions with significant differences were indicated as asterisks.

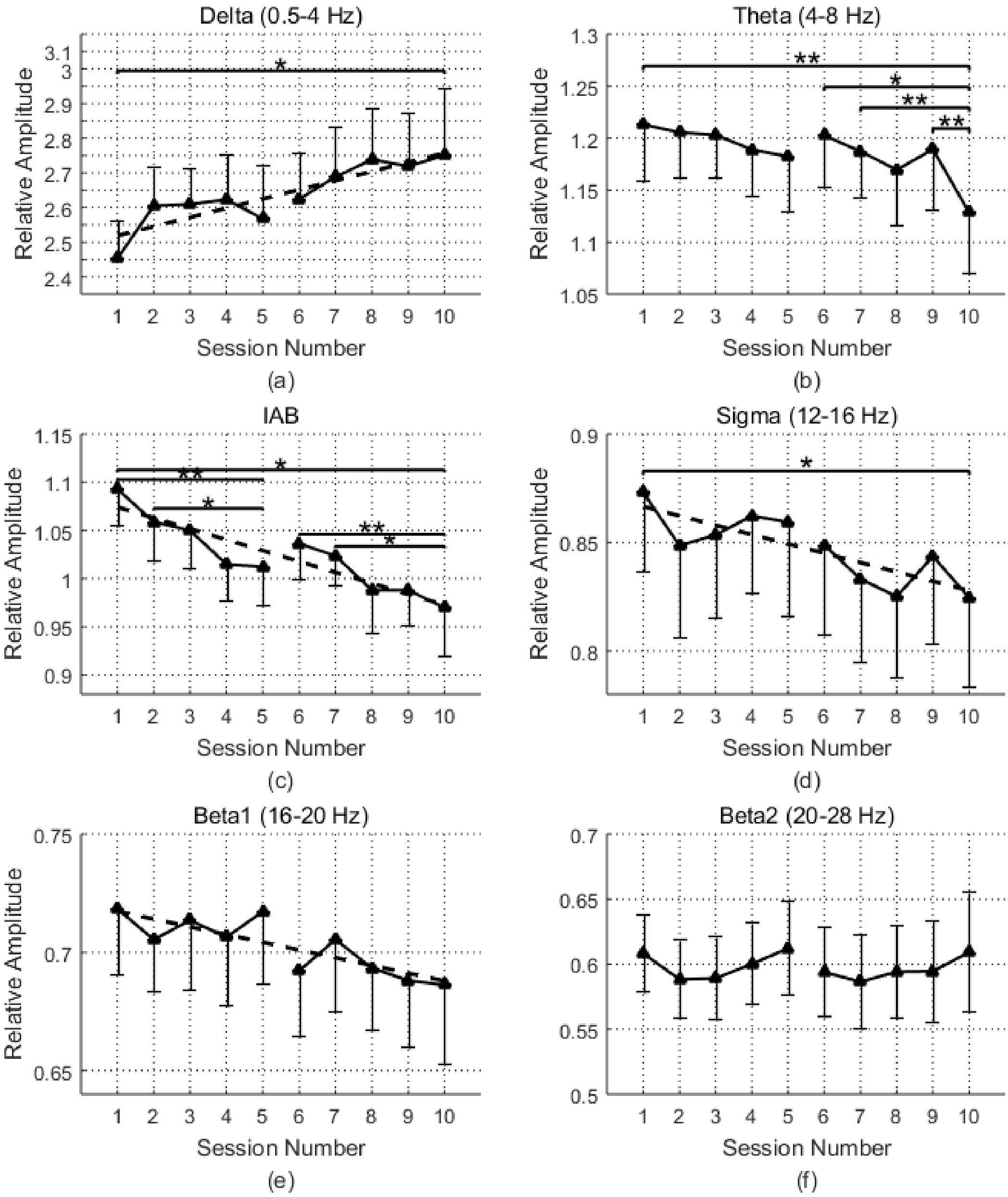

Figure 4-3 Mean relative amplitude of five EEG frequency bands (at channel Oz) in consecutive NF sessions. Dashed straight lines indicate significant correlation between session number and the mean amplitude of corresponding group. The bars indicate standard error of the mean, depicted one-tailed due to the directional trend of corresponding bands. The asterisks indicate significant differences between NF10 and NF01 (*: $p < 0.05$, **: $p < 0.01$).

Table 4-1Pearson correlation between session number and mean relative amplitude

		IAB	Delta	Theta	Sigma	Beta1	Beta2
Group A	*r*	-.933**	.843**	-.969**	-.836**	-0.329	0.005
	p	0.0001	0.0022	0.0000	0.0026	0.3537	0.9880
Group B	*r*	-.817**	.827**	0.062	-.654*	-.847**	-0.526
	p	0.0039	0.0032	0.8659	0.0403	0.0020	0.1185
Total	*r*	-.916**	.889**	-.778**	-.816**	-.828**	0.037
	p	0.0002	0.0006	0.0080	0.0040	0.0031	0.9197

Indicated by Table 4-1, the down-regulation of IAB may lead to the increase of delta band and the suppression of theta, sigma and beta1 bands during NF training sessions. The inverse trend between delta and alpha is in accordance with the previous work [29, 30]. Similarly, the decrease of theta within one-day are also consistent with Gruzelier's work [16]. It is reasonable to speculate that within-session effects of IAB down-regulation NF were not restricted only to the trained IAB band but were also present in lower-frequency or neighbouring spectra.

4.3. SSVEP-BCI Performances

4.3.1. SSVEP Signal SNR

Different analysis time from 1s to 4s with 1s interval were applied for assessment of SSVEP performance. The individual changes of SSVEP SNR and accuracy are as shown in Figure 4-4.

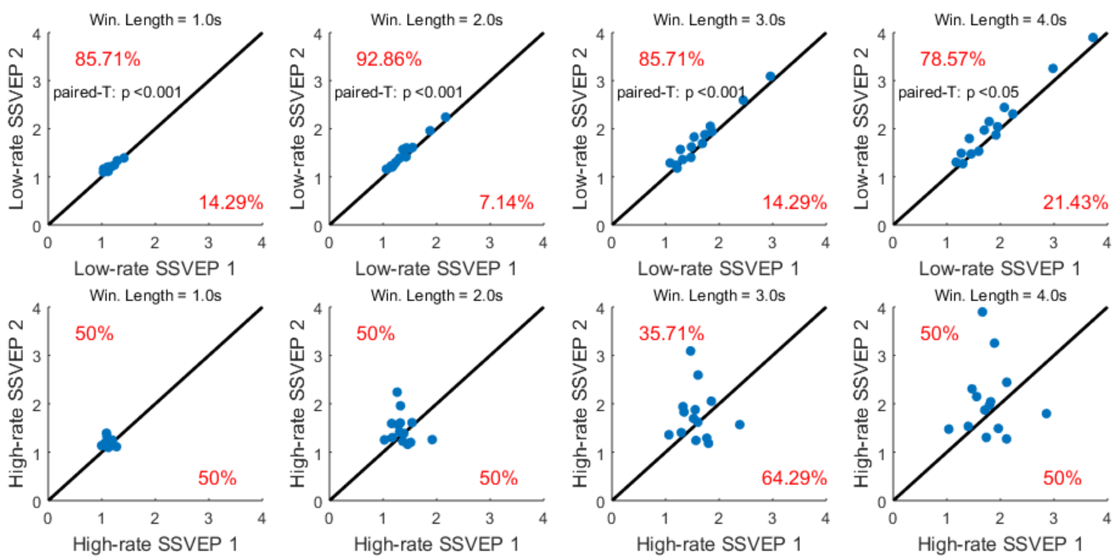

Figure 4-4 Scatter plot illustrates the SSVEP SNR of each subject before and after NFT in window length of 1s, 2s, 3s, and 4s. Plots in upper row is for Group A and in the second two is for Group B. Each dot represents a subject. Paired-t test were applied and only results of significance were displayed.

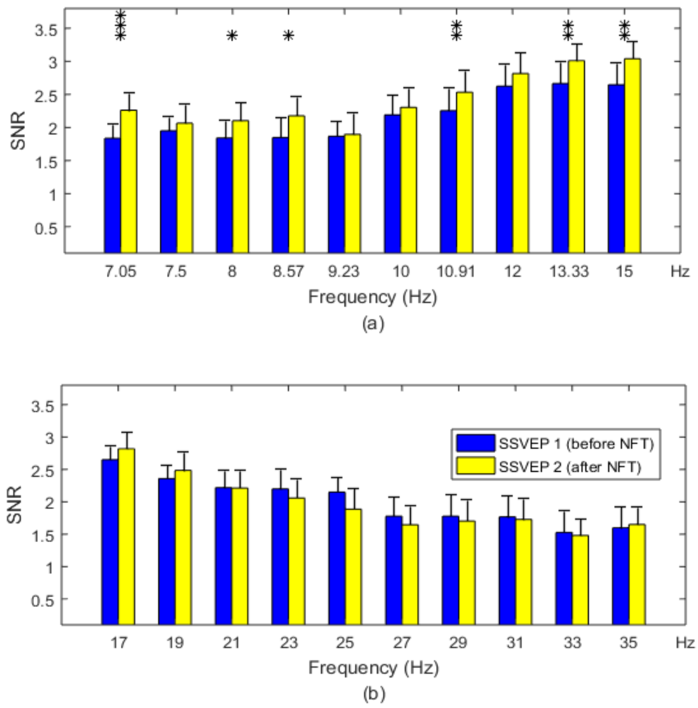

Figure 4-5 Comparisons of the signal SNR in SSVEP2 and SSVEP1. (a) Group A, and (b) Group B. Error bar indicates the standard error of its mean. * represents the significant difference, p < 0.05 and ** represents the significant difference p < 0.01).

In 4-second analysis (as shown in Figure 4-4), the SNR differences between two groups after NF training were obviously different and their change across all stimulus frequencies is shown in Figure 4-5. The SNR of stimulus frequencies within IAB, sigma and beta1 were approximately maintained or improved after NF training while others did not.

4.3.2. Classification Accuracy

The highest SNR is detected and applied to calibrate the classification accuracy across different frequency stimuli, the results are as shown in Figure 4-6.

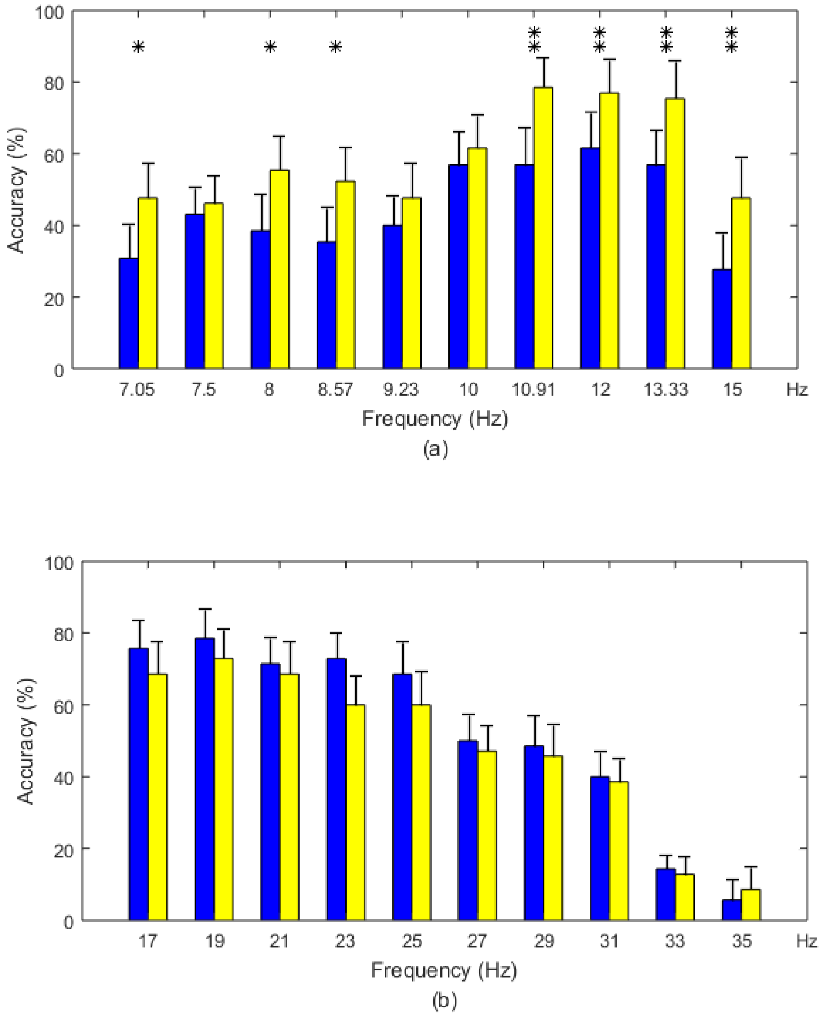

Figure 4-6 Comparisons of the classification accuracy in SSVEP2 and SSVEP1. (a) Group A, and (b) Group B. Error bar indicates the standard error of its mean. * represents the significant difference, p < 0.05 and ** represents the significant difference p < 0.01).

In 4-second analysis, there are only significant improvement in 7.05, 8, 8.57, 10.91, 12, 13.33 and 15 Hz, as shown in Figure 4-6. No significant improvement among any stimulus frequencies in Group B. The accuracy of stimulus frequencies that interfered within IAB, sigma and beta1 were approximately maintained or improved after NF training while others did not. It is noteworthy that, starting from 17 Hz, there also happened to be no significant improvements in NF10 compared with inNF01.

4.3.3. Group Analysis of SSVEP-BCI Performances

The mean SSVEP SNR and the mean BCI classification accuracy in SSVEP1 and SSVEP2 of both Group A and Group B are given in Table 4-2 and depicted in Figure 4-7. After the NFT, 12 out of 13 subjects in Group A showed a better SSVEP signal SNR and 8 of them showed an improved BCI classification accuracy, while 9 out of 14 participants in Group B had a worse SNR and accuracy. A paired t-test revealed a significant improvement in the Group A on SSVEP signal SNR ($t = 4.338$, $p = 0.001$), while no significant improvement in Group B on the SSVEP signal SNR ($t = -0.941$, $p = 0.364$).

Table 4-2 The SSVEP- based BCI performances of each group

Group	Test	SSVEP SNR	Classification accuracy (%)
Group A	SSVEP1 (before NFT)	1.898±0.682	44.8±25.4
	SSVEP2 (after NFT)	2.058±0.720	58.9±25.3
Group B	SSVEP1	1.795±0.405	41.9±39.6
	SSVEP2	1.53±0.391	39.6±18.8

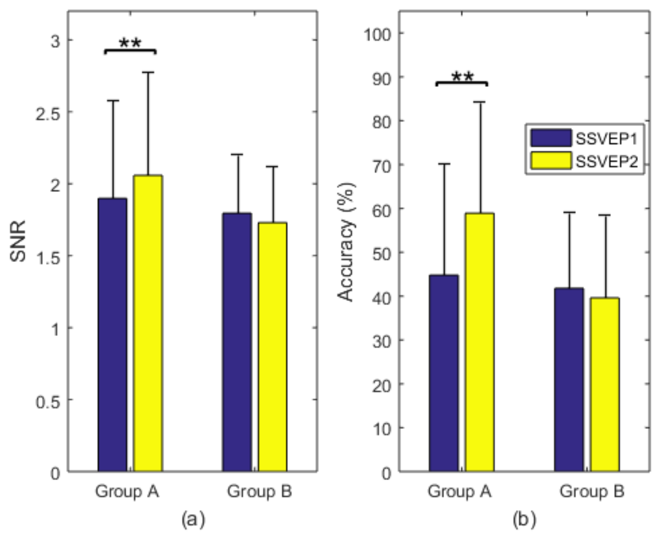

Figure 4-7 Comparisons of the SSVEP-based BCI performance in Group A and Group B, in terms of (a) the SSVEP SNR, and (b) the BCI classification accuracy. (Error bar indicates the SD, ** represents the significant difference, p < 0.01).

No improvement was detected for them in high-frequency SSVEP after NF training. We consider two possible factors: 1. higher-frequency SSVEP response itself are hard to change; 2. high-frequency SSVEP ranges do not interfere with IAB rhythm, thus the suppression of IAB does not affect its performances.

4.3.4. Relationship between SSVEP signal SNR and Classification Accuracy

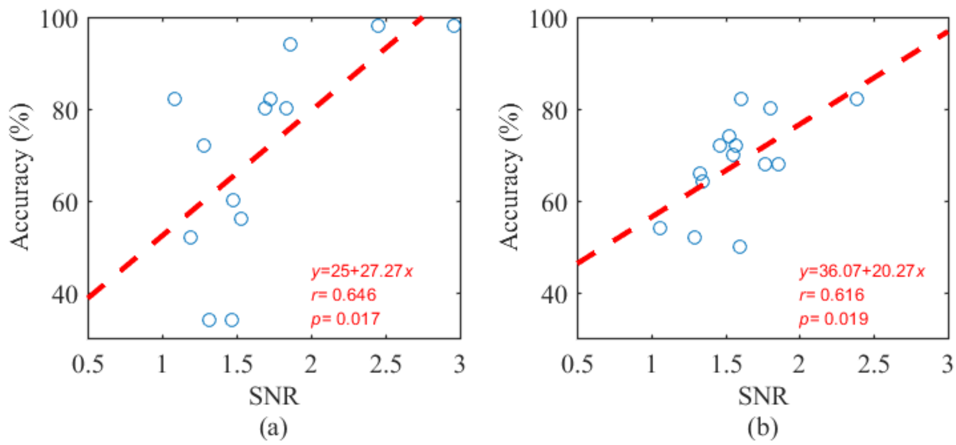

Figure 4-8 Scatter plot illustrates the SSVEP SNR and classification accuracy of (a) Group A: low frequency SSVEP; (b) Group B: high frequency SSVEP. Dashed straight lines indicate linear fitting line with significance in Pearson correlation between SNR and the accuracy of corresponding group. Each dot represents a subject.

SSVEP signal SNR were in positive correlation with BCI classification accuracy in both groups. The regression slope in low-frequency SSVEP (slope=27.27) were larger than it in higher-frequency SSVEP (slope=20.27).

4.4. Resting Initial IAB Predicts SSVEP-BCI Performances

To investigate the relationship between IAB and the initial classification accuracy, Pearson correlation test was applied and suggested there were significant negative correlation between the initial resting IAB in eye-open condition with the low-frequency SSVEP BCI accuracy (r=-0. 697, p=0.008) while no such correlation between higher-frequency SSVEP-BCI (r=-0.176, p=0.547) and resting IAB or other EEG frequency bands.

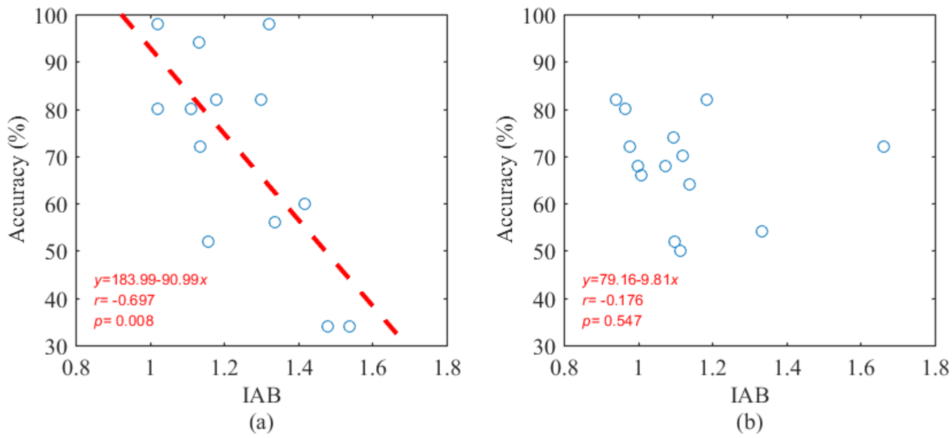

Figure 4-9 Scatter plot illustrates the initial resting IAB and accuracy of: (a) Group A: low frequency SSVEP; (b) Group B: high frequency SSVEP. Each dot represents a subject. Dashed straight lines indicate linear fitting line with significance in Pearson correlation between initial resting IAB and the accuracy of corresponding group. Each dot represents a subject.

Our work in finding predictors SSVEP-BCI classification accuracy were consistent with previous study that only those with low stimulus frequency could be predicted by resting IAB [32].

Compared with previous publication, our first finding was that: NF training could not only enhance the low-frequency SSVEP-BCI performances for participants with ‘low’ initial accuracy but for those who already had ‘high’ initial accuracy before NF training. Yet it is still unclear the mechanism beyond the enhancement of SSVEP performance, which deserves further investigation and more participants should be involved in the higher-frequency SSVEP group.

This study completed a strategy we proposed in previous publication for enhancing the low-frequency SSVEP performances by neurofeedback training and confirms that this approach has effects on general participants. Furthermore, our study reported the performances in high-frequency SSVEP-BCI are less likely to be improved or somehow worsened. Our results indicated the higher the initial IAB, the more enhancement (deterioration) in low-frequency (high-frequency) SSVEP performances. The IAB in initial resting baseline can be an indicator of the NFT effects on SSVEP-BCI classification accuracy, while no resting EEG spectra were found to be correlated with higher-frequency SSVEP-BCI. These findings could be helpful to the SSVEP related studies and would contribute to more effective SSVEP-based BCI applications.

Chapter 5: Organization of the Thesis

The thesis will contain total 7 chapters including the introduction and conclusion:

Chapter 1 introduces the EEG and the general background of EEG and Neurofeedback. Furthermore, important studies on neurofeedback, i.e. predictor for NF training results, amplitude training direction as well as whether the training was unspecific and influences on other EEG bands, were presented.

Chapter 2 overviews the dominant types of BCI and the problem it is faced, i.e. ‘BCI illiteracy’ phenomenon. Various approaches have been proposed and can mainly divided into four aspects: hardware and setup; BCI system design and protocol; signal processing, classification algorithms, and trainings for elicited EEG patterns. And neurofeedback has been proved to be beneficial for certain types of EEG signals in BCI application. Besides, predicting the performance before BCI experiment was a noteworthy study to avoid the frustration on ‘BCI illiteracy’ subjects and enhance the BCI efficacy.

Chapter 3 introduces the details of experimental methods, including participants, EEG recordings, experimental design, the calculation of SSVEP performances, as well as the statistical methods that would be applied to get preliminary results (presented in Chapter 4) in this study.

Chapter 4 shows current results, containing the trainability of IAB in NF training and its influences on other EEG bands, the individual and group analysis of SSVEP performances before and after NFT. In addition, to be complete, relative amplitudes of different EEG bands in resting baselines were also presented.

Chapter 5 reviews frequently used algorithms to build the brain connectivity matrices and estimations to measure the connectivity network based on several graph theory methods.

Chapter 6 presents preliminary brain connectivity results during NF training and SSVEP test.

Chapter 7 finally concludes the whole thesis and indicates the future works.

TIMELINE

- Late - March 2019: Summarize experiment results and modify the manuscript for the paper that would be submitted to Journal of Neural Engineering.

- Early - April 2019: Submit the paper to Journal of Neural Engineering.

- Mid - April 2019: Enrich the results for Coherence and Granger Causality results based on the experiment data.

- Late - April 2019: Organize the content into thesis. Submit the thesis and form the examination committee; Wait for the decision.

- Early - May 2019: Organize the connectivity contents into papers.

- Early - June 2019: Submit the paper of connectivity to journal/conference.

- Mid – June 2019: Defending thesis.

PUBLICATION DURING THE MASTER STUDY

<u>Journal</u>

- Alpha down-regulation neurofeedback training effects on SSVEP-based BCI performances (in preparation)
- Brain connectivity network during neurofeedback training and SSVEP-based BCI measured by coherence and granger causality (in preparation)
- W.Y. Nan, F. Wan, **Q. Tang**, C.M. Wong, B.Y. Wang, and A. Rosa. Eyes-Closed Resting EEG Predicts the Learning of Alpha Down-Regulation in Neurofeedback Training

<u>Conference</u>

- C.M. Wong, **Q. Tang**, J.N. da Cruz, F. Wan. A Multi-channel SSVEP based BCI for Computer Games with Analogue Control.
- X.T. Qu, **Q. Tang**, L. M. Yang, W. Y. Nan, Janir Nuno da Cruz et.al How Mental Strategy Affects Beta/Theta Neurofeedback Training.

<u>Abstracts</u>

- **Q. Tang**, W. Nan, F. Wan, Y. Hu, “Neurofeedback improves SSVEP BCI performance on subjects with both 'high' and 'low' performance,” in Seventh

International BCI Meeting: BCIs: Not Getting Lost in Translation, Pacific Grove, CA, May 21-25, 2018.

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