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Alpha neurofeedback training improves SSVEP-based BCI performance

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Abstract

Objective. Steady-state visual evoked potential (SSVEP)-based brain-computer interfaces (BCIs) can provide relatively easy, reliable and high speed communication. However, the performance is still not satisfactory, especially in some users who are not able to generate strong enough SSVEP signals. This work aims to strengthen a user's SSVEP by alpha down-regulating neurofeedback training (NFT) and consequently improve the performance of the user in using SSVEP-based BCIs. *Approach.* An experiment with two steps was designed and conducted. The first step was to investigate the relationship between the resting alpha activity and the SSVEP-based BCI performance, in order to determine the training parameter for the NFT. Then in the second step, half of the subjects with 'low' performance (i.e. BCI classification accuracy <80%) were randomly assigned to a NFT group to perform a real-time NFT, and the rest half to a non-NFT control group for comparison. *Main results.* The first step revealed a significant negative correlation between the BCI performance and the individual alpha band (IAB) amplitudes in the eyes-open resting condition in a total of 33 subjects. In the second step, it was found that during the IAB down-regulating NFT, on average the subjects were able to successfully decrease their IAB amplitude over training sessions. More importantly, the NFT group showed an average increase of 16.5% in the SSVEP signal SNR (signal-to-noise ratio) and an average increase of 20.3% in the BCI classification accuracy, which was significant compared to the non-NFT control group. *Significance.* These findings indicate that the alpha down-regulating NFT can be used to improve the SSVEP signal quality and the subjects' performance in using SSVEP-based BCIs. It could be helpful to the SSVEP related studies and would contribute to more effective SSVEP-based BCI applications.

Keywords: brain-computer interface (BCI), steady-state visual evoked potential (SSVEP), neurofeedback training (NFT), individual alpha band (IAB), BCI performance

(Some figures may appear in colour only in the online journal)

1. Introduction

Although brain-computer interface (BCI) research has made significant progress recently, most of the developed systems

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remain in laboratory research and demonstration stages. The performance of the current state-of-the-art is still low and far from the expectation. Moreover, it has been found that a substantial percentage of subjects appear incapable of utilizing a BCI, namely the 'BCI illiteracy' problem. For instance, a number of recent studies show that around 10% to 25% of users are unable to attain effective control (Guger *et al* 2003, 2009, Kelly *et al* 2005, Allison *et al* 2010a, Allison and Neuper 2010b, Brunner *et al* 2010, Volosyak 2011, Ahn *et al* 2013).

To improve BCI performance, tremendous research efforts have been made and many sound results have been reported. However, the majority of the existing work has been devoted to hardware and system design, signal processing and classification algorithms. Unfortunately, successful BCI operations depend significantly on how well the users can voluntarily modulate their neural activity (Neuper and Pfurtscheller 2010) or passively produce the wanted brainwaves. If a user is not able to generate strong enough signals that are classifiable, even the best system design and algorithms cannot lead to satisfactory results (Neuper and Pfurtscheller 2010).

A different approach to enhancing the performance of BCIs is 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, 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). The 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 (Vernon 2005, Nan *et al* 2012, 2013, Ros *et al* 2014, Gruzelier 2014) as well as in treatment of mental disorders such as attention-deficit/hyperactivity disorder (ADHD) (Arns *et al* 2014), autistic spectrum disorder (Coben *et al* 2010), and major depressive disorder (Peeters *et al* 2014).

In recent years, NFT has been applied to improve the performance of various types of BCIs. Motor imagery (MI)-based BCIs and slow cortical potential (SCP)-based BCIs first went into consideration and later became intensively studied due to their underlying voluntary nature in EEG pattern generation (Neuper and Pfurtscheller 2010). Hwang *et al* (2009) proposed a neurofeedback-based MI training system which can help subjects to learn how to self-regulate the mu rhythm during motor imagination. Blankertz *et al* (2010), Grosse-Wentrup and Schölkopf (2012), and López-Larraz *et al* (2013) proposed the neurofeedback protocols for the subjects to modulate the resting state of sensorimotor rhythm (SMR), the gamma band activity, and the upper alpha band activity, to improve the performance in using MI-based BCIs, respectively. For SCP-based BCIs, the subjects were asked to learn how to control the SCP voluntarily through NFT (Birbaumer *et al* 1999, Birbaumer 2006). Besides, Egner and Gruzelier (2001) suggested enhancing the subject's P300 amplitude during an auditory oddball task through SMR and beta NFT.

Among various types of noninvasive BCIs, steady-state visual evoked potential (SSVEP)-based BCIs can provide a relatively high speed of communication. A recent benchmark was due to Chen *et al* (2015), who had achieved an information transfer rate (ITR) up to 5.32 bits per second, the highest ITR reported in either noninvasive or invasive BCI spellers. It left a limited room for further improvement in SSVEP-based BCI system design and optimization. On the other hand, the subject side appears very promising but was little explored. Fernandez-Vargas *et al* (2013) designed a closed-loop optimization protocol to improve the efficiency of SSVEP-based BCIs, which consisted of two closed-loops, one for selecting the most compatible stimulus frequencies and another for an online auditory feedback of SSVEP amplitudes. Yet the NF like effect was shadowed due to the mixture of two closed-loops. Another relevant work from Yin *et al* (2015) utilized a real-time biofeedback of SSVEP amplitudes to increase a user's visual selective attention on the target stimulus, but no significant improvement in accuracy was found. The authors explained the possible reason by the variation in user's attention since this real-time biofeedback mechanism may have only been helpful when the reduction in a subject's attention had a significant effect on the SSVEP detection.

Unlike the research of Fernandez-Vargas *et al* (2013) and Yin *et al* (2015) in which the SSVEP amplitude was directly taken as the feedback parameter, this study adopted a standard procedure to design and apply NFT to improve SSVEP-based BCI performance. More specifically, we first investigated the relationship between SSVEP-based BCI performance and the brain oscillations, in order to find the key NFT parameters including the training feature and training direction. Then we applied the NFT to help subjects to self-regulate the selected EEG patterns, with the SSVEP-based BCI performance evaluated before and after the NFT. This was inspired by some recent results especially about the prediction of SSVEP-based BCI performance. For instance, Makeig *et al* (2002) and Yeung *et al* (2004) pointed out that alpha band (7.5–12.5 Hz) may play an important role in evoked potentials. Zhang *et al* (2013) further confirmed a negative correlation between the resting upper alpha amplitude and the classification accuracy of SSVEP-based BCI.

However, the above studies utilized the fixed alpha frequency band. As pointed out by Klimesch (1999), the alpha frequency band has a large inter-individual difference and it was suggested to adjust the frequency windows of alpha for each subject by using the individual peak alpha frequency (PAF) as an anchor point. On the other hand, Morgan *et al* (1996) found the SSVEP response strongly correlated with visual attention, and Plotkin (1976) showed that the attention was negatively correlated with the occipital alpha rhythm. Therefore, in this study we first investigated the relationship between the resting individual alpha band (IAB) amplitude and the SSVEP-based BCI performance described by the

SSVEP signal-to-noise ratio (SNR) and the BCI classification accuracy. Then we proposed to use the NFT to decrease users' IAB amplitude in the occipital area. The hypothesis is that this decrease in IAB activity can lead to an increase of the SSVEP SNR, and eventually the performance enhancement of the users especially for whom cannot attain effective control of SSVEP-based BCIs.

2. Materials and methods

2.1. Participants

A total of 33 healthy adults (age: 24.9 ± 3.9 years; 11 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. All subjects 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).

2.2. EEG signal acquisition

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 the baseline recording and the SSVEP-based BCI test, and 256 Hz in the NFT part. 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 high-frequency noise, baseline drift and power line interference.

2.3. Experimental design

2.3.1. Experimental procedure. The main objective of this study is to apply NFT to improve a subject's performance in using SSVEP-based BCI which is evaluated by BCI classification accuracy and SSVEP SNR. To this goal, there were two steps in the experiment. In the first step (Step_1 for short), we firstly recorded the resting baseline (Baseline_1) and then performed the SSVEP-based BCI test (Test_1) for 33 participants. The resting baseline including 1 min of eyes-open epoch and 1 min of eyes-closed epoch were recorded at the electrode Oz. The objective of Step_1 was to find out the relationship between the SSVEP-based BCI performance and the resting alpha activity in order to determine the NFT feature and direction.

In Step_2, 20 subjects with low classification accuracy (i.e. classification accuracy <80%) from Step_1 were then equally and randomly allocated to a NFT group (age: 25.5 ± 3.6 years, 4 females) and a non-NFT control group (age: 24.1 ± 2.6 years, 5 females). In the NFT group, after Baseline_1 and Test_1, the subjects completed the NFT in two consecutive days. After all training sessions, the subjects repeated the baseline recording (Baseline_2) and the BCI test (Test_2). To assess the effectiveness of the NFT, the non-NFT control group went through the experiment with the same arrangement, however, without any training sessions.

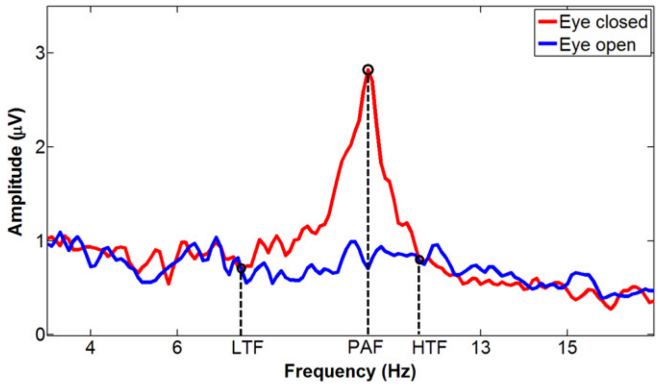

Figure 1. The determination of the individual alpha band.

2.3.2. SSVEP-based BCI test. In the SSVEP-based BCI test, ten frequencies between 7 and 15 (Hz), i.e. 7.05, 7.5, 8, 8.57, 9.23, 10, 10.9, 12, 13.33 and 15 (Hz) were selected as the visual stimuli, and 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 aforementioned 10 stimulus frequencies. 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 subjects where they should focus their gaze.

2.3.3. NFT. The training parameter was the relative IAB amplitude at Oz as calculated by the following equation:

$$\text{Relative IAB amplitude} = \frac{\sum_{k=LTF/\Delta f}^{HTF/\Delta f} X(k)}{HTF - LTF} \Bigg/ \frac{\sum_{k=0.5/\Delta f}^{30/\Delta f} X(k)}{30\text{--}0.5} \quad (1)$$

where LTF and HTF denote the low transition frequency and the high transition frequency of the IAB expressed in Hz, $X(k)$ is the frequency spectrum amplitude calculated by FFT with a 1 s sliding window that shifted every 0.125 s, Δf is the frequency resolution of FFT and k is the spectrum index. As shown in figure 1, the LTF and HTF for calculating IAB were determined for each subject through the amplitude band crossings of the eyes-open and eyes-closed baseline

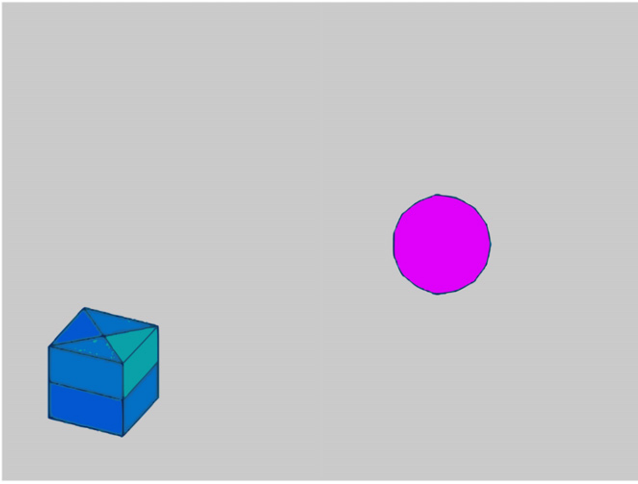

Figure 2. Visual cue of the NFT paradigm.

recordings, and the PAF showed the largest amplitude between the LTF and HTF in the eyes-closed condition.

For the NFT schedule, each subject performed 5 NFT sessions each day in two consecutive days for a total of 10 training sessions, and each NFT session consisted of 3 successive 1-min trials with a 5-s interval between trials.

The feedback interface contained a sphere and a cube, as shown in figure 2. The radius of the sphere reflected a real-time feedback of the training parameter. If the training parameter was below the threshold (Goal_1), the sphere changed its colour, and its size increased as the training parameter decreased. The height of the cube increased whenever the feedback parameter stayed below the threshold for more than 2 s (Goal_2). Thus, the ultimate goal for the subjects was to elevate the cube as high as possible (Rodrigues *et al* 2010). The subjects were thus expected to apply spontaneous mental strategies to achieve the goals, while no specific mental strategies were prescribed. They were asked to utilize one mental strategy in a 1-min trial and could change it in the next trial if the current one was not successful to achieve Goal_1. After each training session, the mental strategies used in the three trials were written down with the effects scored by the subjects.

The feedback threshold in the first training session was set to the mean relative IAB amplitude in the eyes-open resting baseline. The threshold would be decreased by 0.05 in the next session if the percentage of time that the relative IAB amplitude stayed below the threshold exceeded 60%, or increased by 0.05 if the percentage of time was less than 20%.

2.4. SSVEP data processing

2.4.1. SSVEP signal SNR calculation. In order to reduce the effects of adverse interference such as muscular artifacts, trials with EEG amplitude exceeding 100 μV were excluded from the analysis. To minimize the effect of the background EEG activity across subjects, the quality of SSVEP responses was described using SNR, defined as the ratio between the power of the stimulus frequency and the mean power of a 2 Hz frequency interval centered on the stimulus frequency but excluding the stimulus frequency, which can be calculated as

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

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 the following analysis, the SSVEP SNR of each subject was computed as the mean across the six electrodes and the ten frequencies.

2.4.2. SSVEP-based BCI accuracy calculation. The canonical correlation analysis (CCA), a widely used multivariate statistical method in SSVEP-based BCIs, was used for classification (Bin *et al* 2009). In addition, a 4-s time window was chosen in CCA and for each subject the classification accuracy was calculated from 50 trials.

3. Results

3.1. The relationship between the resting relative IAB amplitude and the BCI performance

For the 33 subjects in Step_1, their BCI classification accuracy ranged from 38% to 100% (mean = 74.91%, SD = 16.23%) and their relative IAB amplitude at Oz in the eyes-open resting state varied from 0.78 to 1.39 (mean = 1.046, SD = 0.168). Shapiro-Wilk test indicated that the data were normally distributed. Thus, a 2-tailed Pearson correlation test was employed to examine the relationship between the relative IAB amplitude at Oz and the BCI performance. As shown in figures 3(a) and (b), the relative IAB amplitude had a significant negative correlation with the SSVEP SNR ($r = -0.423$, $p = 0.014$) and the classification accuracy ($r = -0.579$, $p < 0.001$).

3.2. NFT result

3.2.1. EEG changes. The relative IAB amplitude at Oz for each subject in each session and its mean across all subjects in the NFT group are depicted in figure 4, which presented a decreasing trend over 10 training sessions for all subjects. A 2-tailed Pearson correlation test further found a significant negative correlation between the mean relative IAB amplitude and the session number ($r = -0.921$, $p < 0.001$), suggesting that the subjects were able to decrease their alpha activity by this training protocol.

Regarding the relative IAB amplitude at Oz during the eyes-open resting baseline, no significant difference was found between Baseline_1 and Baseline_2, in either the control group ($t = 0.014$, $p = 0.989$) or the NFT group ($t = 1.661$, $p = 0.131$).

3.2.2. BCI performance changes. The changes of all subjects' SSVEP-based BCI performance in the NFT and

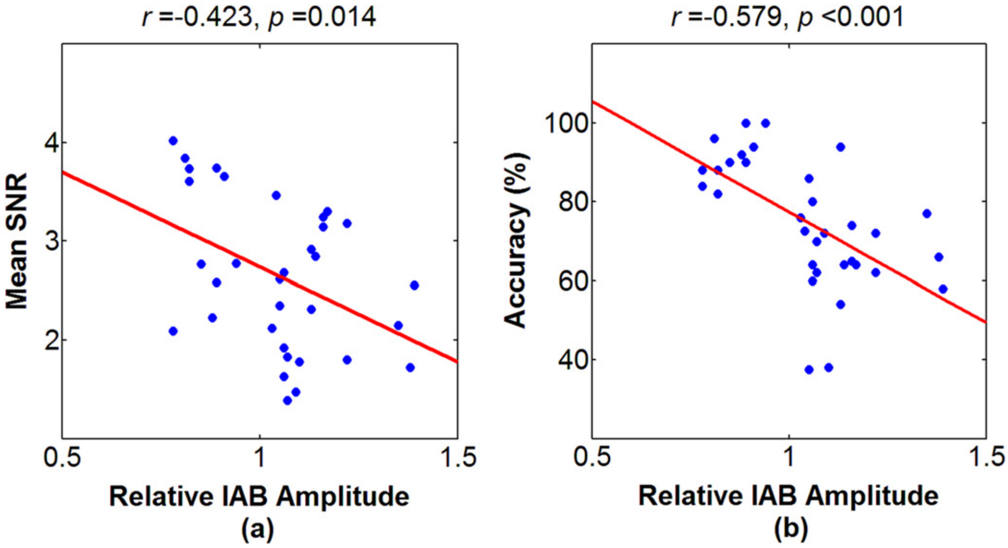

Figure 3. Scatterplots of the relative IAB amplitudes at Oz in the eyes-open resting state versus. (a) the SSVEP SNRs, and (b) the SSVEP-based BCI classification accuracy. The straight lines represent the fitted trend lines.

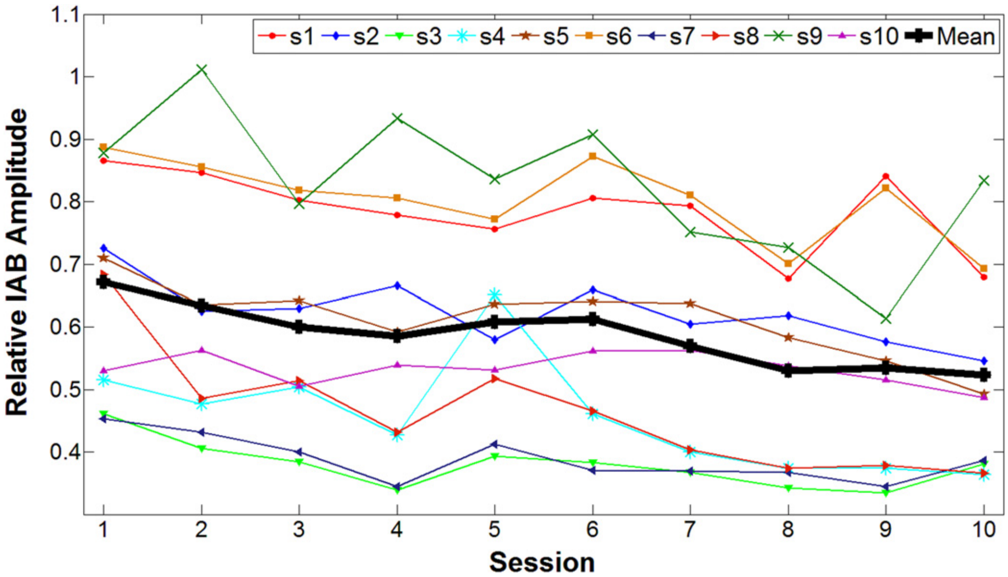

Figure 4. The relative IAB amplitudes in each training session for 10 subjects in the NFT group (colour curves) and the mean of the relative IAB across all subjects (black thick curve).

control groups are shown in figure 5. The mean SSVEP SNR and the mean BCI classification accuracy in Test_1 and Test_2 of both NFT and control groups are given in table 1 and depicted in figure 6. As shown in figure 5, all subjects in the NFT group showed SSVEP SNR and BCI accuracy improvements which cannot be found in the control group. Independent *t* test found that both the SSVEP signal SNR and the classification accuracy in Test_1 had no significant difference between the two groups. After the NFT, however, the NFT group showed an average increase of 16.49% in the SSVEP signal SNR and an average increase of 20.33% in the BCI classification accuracy. A paired *t*-test revealed a significant improvement in the NFT group on both the SSVEP signal SNR ($t = 4.856$, $p = 0.001$) and the BCI classification accuracy ($t = 12.249$, $p < 0.001$), while no significant improvement in the control group on the SSVEP signal SNR ($t = 0.762$, $p = 0.465$) and the BCI classification accuracy ($t = 0.067$, $p = 0.948$).

Furthermore, according to the 1-tailed Pearson correlation test results, the decrease in the relative IAB amplitude from Session 1 to 10 had a close-to-significant correlation with the improvement in the SSVEP signal SNR ($r = 0.523$, $p = 0.06$) and the BCI classification accuracy ($r = 0.477$, $p = 0.082$). Additionally, in the sub-band of IAB (i.e. the lower IAB from LTF to PAF), the relative amplitude decrease from Session 1 to 10 showed a close-to-significant correlation with the SSVEP signal SNR improvement ($r = 0.541$, $p = 0.053$) and a significant correlation with the BCI classification accuracy improvement ($r = 0.583$, $p = 0.039$).

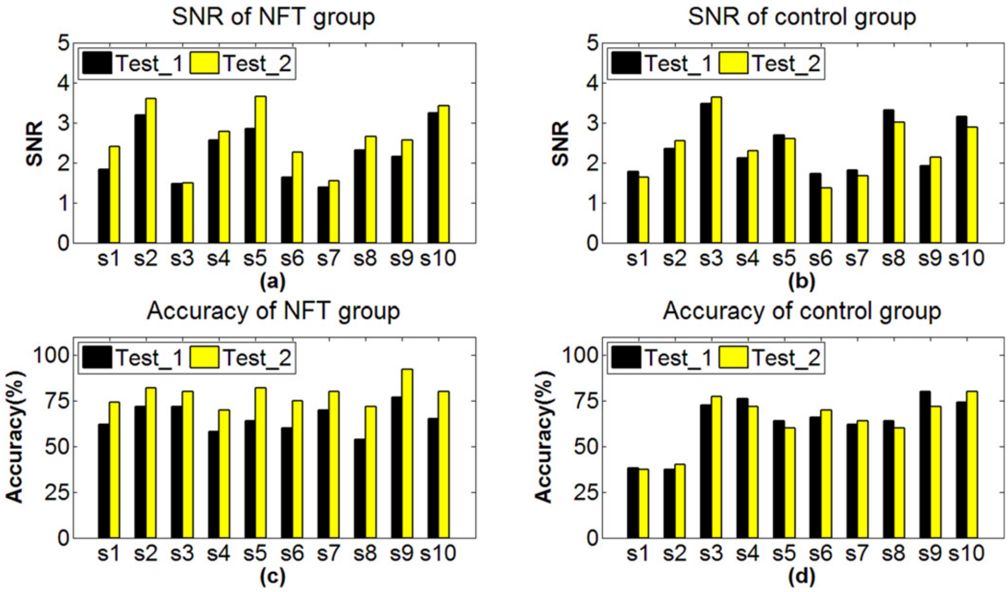

Figure 5. The SSVEP-based BCI performance of all subjects in the NFT and the control groups: (a) the SSVEP SNR of the NFT group, (b) the SSVEP SNR of the control group, (c) the BCI classification accuracy of the NFT group, and (d) the BCI classification accuracy of the control group.

Table 1. The SSVEP-based BCI performance of each group.

Group	Test	SSVEP SNR	Classification accuracy (%)
NFT	Test_1 (before NFT)	2.262 ± 0.685	65.4 ± 7.2
	Test_2 (after NFT)	2.635 ± 0.763	78.7 ± 6.3
Control	Test_1	2.431 ± 0.674	63.4 ± 14.7
	Test_2	2.378 ± 0.702	63.3 ± 14.6

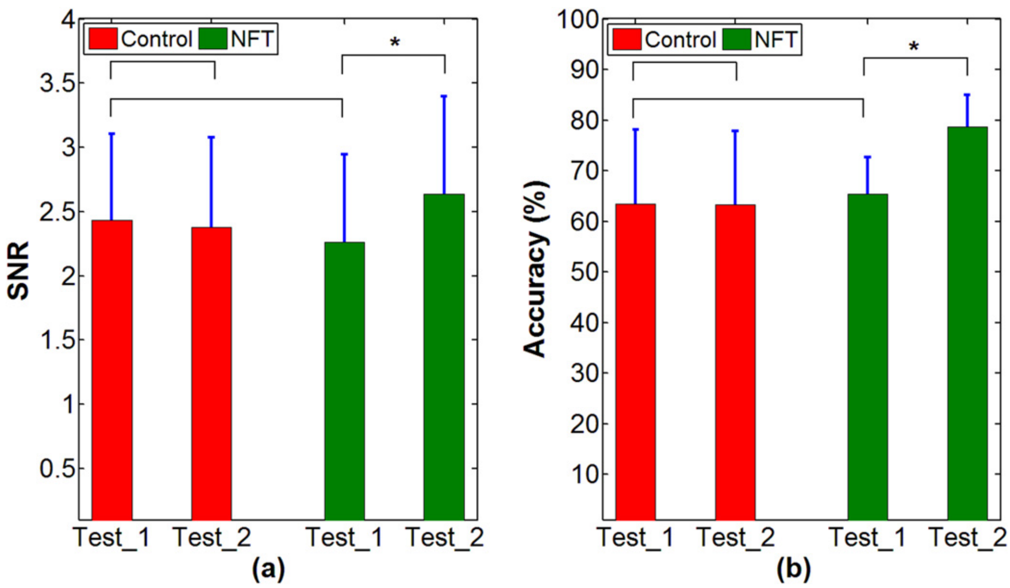

Figure 6. Comparisons of the SSVEP-based BCI performance in the NFT and the control groups in terms of (a) the SSVEP SNR, and (b) the BCI classification accuracy. (Error bar indicates the SD, * represents the significant difference, $p < 0.05$).

4. Discussion

The relation between the resting-state EEG activities and the potential processing abilities of the brain has been extensively reported in the literature. Relevant to SSVEP-based BCIs, recently Fenandez-Vargas *et al* (2013) found the correlation between resting-state EEG bands and the BCI performance, and Zhang *et al* (2013) further proposed the prediction of subjects' SSVEP-based BCI performance by the resting-state EEG network measures.

This study investigated the relationship between the SSVEP-based BCI performance and the resting alpha activity in a total of 33 subjects. As shown in figure 3(b), it was observed that most subjects with relatively low relative IAB amplitude (<1.0) obtained relatively high classification accuracy (>80%). What's more, we found that the alpha amplitude at Oz in the eyes-open resting baseline had significant negative correlations with the SSVEP SNR and the BCI classification accuracy under 10 stimulus frequencies between 7 Hz and 15 Hz, suggesting that the relative IAB amplitude at Oz in the resting state could be a potential predictor of the SSVEP-based BCI performance. A similar result was reported by Zhang *et al* (2013), where the mean relative power spectral densities in the upper alpha band (9–12.5 Hz) was found correlated close-to-significance for the Oz ($r = -0.535$, $p = 0.073$), and significantly for the mean across the nine electrodes from parietal to occipital regions ($r = -0.638$, $p = 0.026$) with the classification accuracy under the four stimulus frequencies (7.5, 10, 12 and 15 Hz) in the eyes-closed condition. Furthermore, our findings are in line with a recent study from Won *et al* (2016) who reported a negative correlation between the occipital resting alpha power and the classification accuracy in the low stimulus frequency range (6–14.9 Hz). Interestingly, in their work such a correlation could not be found in high stimulus frequency (26–34.7 Hz). Therefore, the relationship between the EEG power spectrum and the SSVEP-based BCI performance may depend on the stimulus frequency.

The precise neurobiological mechanism of the relations remains unclear, yet previous studies provide some interesting hints. It was reported that prestimulus alpha activity is inversely related to visual perception performance, such as attentional blink (AB), visual attention, visual discrimination, and visual detection performance (Ergenoglu *et al* 2004, Thut *et al* 2006, van Dijk *et al* 2008, Hanslmayr *et al* 2011, Macdonald *et al* 2011). Moreover, the resting alpha activity was found negatively correlated with the accuracy and positively correlated with the AB magnitude in AB task (MacLean *et al* 2012). These findings implied that the prestimulus alpha activity in the occipito-parietal cortex co-varies with the excitability of the visual cortex (Klimesch *et al* 2007, Romei *et al* 2008, 2010) and the alpha reductions may accompany an increase in vigilance, which increases their attention-demanding cognitive processes (MacLean *et al* 2012). The speculation was that the prestimulus and the resting alpha activity in the occipito-parietal cortex were associated with the performance for visual tasks, like the tasks during the SSVEP-based BCI tests. Besides, the negative correlation between the prestimulus alpha activity and VEP (or EP) was found in Brandt and Jansen (1991), Başar *et al* (1998), and Barry *et al* (2000), which may imply that the SSVEP amplitude is negatively correlated with the prestimulus alpha activity since there is a strong association between SSVEP and VEP (Vialatte *et al* 2010). However, Becker *et al* (2008) found that the relationship between prestimulus alpha and VEPs is not straight forward. One possibility is that the VEP signal parameters could be modulated by different types of visual tasks. This issue is still in debate and requires more investigations in the future.

The subjects with low BCI classification accuracy (<80%) were selected and performed NFT for decreasing their relative IAB amplitude at Oz. As expected, it was found that the subjects were able to decrease their alpha amplitude during training. This alpha decrease is consistent with Ros *et al* (2013) in which the fixed alpha band (8–12 Hz) was trained to decrease by a 30 min training session. During the NFT, the subjects focused their attention on the feedback display while applying mental strategy to achieve Goal_1 and Goal_2. Thus, their high attention and active mental activity may be responsible to the alpha decrease since this has been proven to be linked to increased attention (Thut *et al* 2006) and active cognitive processing (Klimesch *et al* 2007). Moreover, the mechanism of NFT is operant conditioning in the learning theory of behaviorism. When the produced changes in the EEG meet the reward condition (i.e. the relative IAB amplitude stays below the predefined threshold), a reward stimulus is presented immediately following the responses (e.g. the sphere color changes and its size increases) (Sterman and Egner 2006). Under this operant learning paradigm, the subject would learn how to decrease their alpha amplitude by NFT.

On the contrary, the resting relative IAB amplitude showed no significant change after the NFT, in line with previous studies which demonstrated that the resting alpha went back to the initial level after a 30 min session of alpha down-regulating NFT (Ros *et al* 2013, Kluetsch *et al* 2014). Nonetheless, the NFT group gained a significant performance enhancement in both SSVEP SNR and classification accuracy which was not observed in the control group. Even though the resting alpha amplitude showed a rebound after training, the increased corticospinal excitability and decreased intracortical inhibition (Ros *et al* 2010), the increased calmness and network connectivity (Ros *et al* 2013, Kluetsch *et al* 2014) as well as the increased metabolic rate associated with alpha decrease in the NFT (Klimesch *et al* 2007) may result in the performance enhancement. More interestingly, we found that the improvement in the SSVEP SNR and the BCI classification accuracy were associated with the lower IAB decrease from Session 1 to Session 10, which further proved that the improvement in the SSVEP-based BCI performance resulted from the NFT.

In the literature, various methods from different aspects have been proposed to improve the SSVEP-based BCI performance, such as visual stimulation optimization (Marteka and Byczuk 2006, Lee *et al* 2011), signal processing (Bashashati *et al* 2007, Liu *et al* 2014), and adaptation and customization of the BCI systems (Volosyak 2011, Zhang *et al* 2014, da Cruz *et al* 2015). As the NFT in this study was proposed from a different viewpoint aiming to strengthening the subject's EEG patterns, a combination of the proposed NFT with any of the above methods should be able to provide more efficient SSVEP-based BCIs.

It should be noted that, in order to evaluate the NFT effects more precisely, only one stimulus was presented per time in the BCI test, to reduce the interference due to other factors such as attention shift among multiple stimulus targets, especially for the naive subjects. On the other hand, according to Ng *et al* (2011), the SSVEP response would not be much affected by other flashing targets if the inter-stimulus distance is larger than 6 cm. Therefore, the proposed NFT should remain effective when multiple stimulus targets are presented in a typical SSVEP-based BCI. Furthermore, like in most existing research in SSVEP-based BCIs, this study adopted ten stimuli frequencies between 7 and 15 Hz because the amplitude of the SSVEP signal evoked by the visual stimulus flashing at low frequency (6–15 Hz) has been known higher than that of the medium frequency (15–40 Hz) as well as the high frequency (40–60 Hz) and in consequence normally better BCI system performance (Gao *et al* 2003, Yin *et al* 2013). It is not clear whether and how effectively the proposed alpha down-regulating NFT could improve the SSVEP-based BCI performance with higher stimulus frequencies, which deserves further investigation.

5. Conclusion

This study showed that the resting relative IAB amplitude has a negative correlation with the SSVEP-based BCI performance and the proposed alpha down-regulating NFT could lead to improvement of SSVEP signal SNR and BCI classification accuracy. Our results suggest a promising approach to further improving SSVEP-based BCI performance additional to the current efforts on the system design and optimization. The resting relative IAB amplitude has the potential to be a simple predictor of the SSVEP-based BCI performance. These findings could be helpful to the SSVEP related studies and would contribute to more effective SSVEP-based BCI applications.

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