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Towards improvement of MI-BCI performance of subjects with BCI deficiency

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Abstract— **The subjects' performance in using a brain-computer interface (BCI) system controlled by motor imagery (MI) varies considerably. Poor subjects' performance, known as BCI deficiency, can be due to the subjects' inability to modulate their sensorimotor rhythms (SMRs). In this work, we investigated the feasibility of improving the BCI performance through neurofeedback (NF) training of the resting state alpha rhythm (8–13 Hz). Thirteen healthy subjects were recruited and randomly assigned to the experimental or the control group. The experimental group participated in a MI-BCI session, followed by 12 NF sessions, and a final MI-BCI sessions. The control group performed a MI-BCI session followed by a final MI-BCI session. The results showed that the performances of the experimental group after 12 sessions of NF significantly improved upon the initial MI-BCI performance (p=0.02) but not the control group (p=0.14). Moreover, the resting state alpha of the experimental group significantly improved after 12 sessions of NF (p=0.04). In conclusion, the proposed approach is promising to address BCI deficiency.**

I. INTRODUCTION

Motor imagery (MI) or imagination of movement is one of the mental activities for controlling an electroencephalogram (EEG)-based brain-computer interface (BCI) system [1]–[3]. Performing MI results in event-related desynchronization (ERD) and event-related synchronization (ERS) of EEG rhythms [4]. In other words, stronger ERD/ ERS indicates how well a subject performs MI task and subsequently controls an EEG-based MI-BCI. However, there is a large variation in MI-BCI performance of the subjects [5], and the reason why some subjects cannot use MI-BCI to achieve even moderate performance is not well studied. BCI deficiency, the subjects' inability to modulate their brain rhythms, is one of the main reasons of poor MI-BCI performance [6], which limits the applicability of BCI technology.

Several performance predictors have been proposed to predict the BCI performance of the subjects and also detect those subjects with BCI deficiency. Having some prior knowledge about the performance of the subjects may lead us to investigate other possible reasons of performance variation in different subjects and also yield in designing a novel experiment, which aimed to help users with BCI deficiency. The Resting state sensorimotor rhythm (SMR) over sensorimotor area has been proposed as a neurophysiological performance predictor for a MI-BCI system [7]. They showed that higher resting state SMR in relax with eyes-open condition positively correlated to MI-BCI performance of the subjects. Therefore, the subjects with poor BCI performance can be detected through a short resting state EEG recording. Gamma band power was introduced as another neurophysiological performance predictors for MI-BCI [8]. Psychological predictors [9], [10] have also been proposed for subjects' performance prediction. However, none of the above mentioned predictors has been used in practice to help subjects improve their BCI performance.

The applicability of BCI technology can be broaden through helping subjects with BCI deficiency improve their performance. Operant conditioning is one of the methods through which the subjects can learn to modulate their brain rhythms [11], [12] and thus enhance their BCI performance. Machine learning algorithms such as adaptive classification algorithms have been proposed to enhance the BCI performance of the subjects [13], [14]. However, there is not enough evidence to show these adaptive methods can help subjects modulate their brain rhythms. In contrary, co-adaptation is a promising method proposed to address BCI deficiency [15] [16], it adapts both user and the algorithms of the BCI system. It has shown by using the co-adaptive method [15], only half of the subjects with BCI deficiency achieved BCI performance above 70% which is an acceptable threshold in the BCI control [11]. Therefore, finding a method to address BCI deficiency and thus help subjects improve their performance is still highly valuable.

In this work, we sought to investigate the feasibility of improving the BCI performance of the subjects by enhancing their resting state alpha rhythm. To the best of our knowledge the impact of improving the resting state SMR on the MI-BCI performance has not been studied so far. Neurofeedback (NF) is one of the plausible methods used for regulating the brain rhythms such as alpha rhythm [17]. During several NF training sessions, a subject may explore distinctive strategies to figure out how to regulate his brain rhythms. NF has been previously used for regulating SMRs [18]–[20]. In light of the positive effects of NF on regulating the brain rhythms, we aimed to a design a novel experiment to enhance the resting state alpha rhythms using NF training and investigate its impacts on MI-BCI performance of the subjects with BCI deficiency.

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II. METHODS

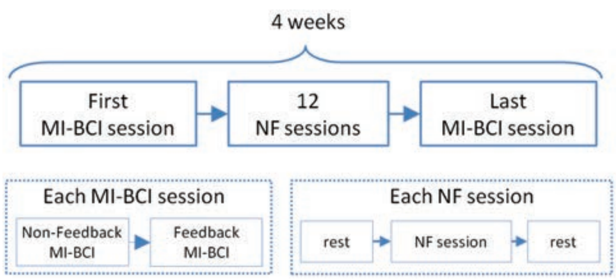
A. Experimental setup

We conducted an experiment to enhance the resting state alpha rhythm (8–13 Hz) of the subjects using NF training. Thirteen healthy subjects (6 female, 7 male; mean=26.46 years, SD=3.28) were randomly assigned to either (1) experimental group (N=6) or to (2) control group (N=7) and written consent was sought. Only two of the subjects from the experimental group had prior BCI experiences and the rest of the participants were BCI novices and all of them had not performed NF experiment before.

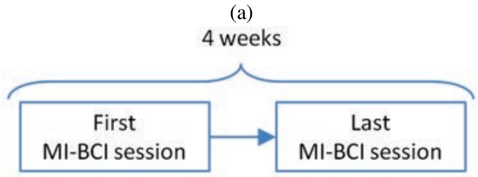
Fig. 1(a) and (b) shows the proposed experiment flow diagram. The experimental group participated in a MI-BCI session followed by 12 NF sessions, and another MI-BCI session. The control group performed a MI-BCI session followed by a final MI-BCI session one month later. By recruiting the control group we can validate that the performance improvement of the experimental group is mainly because of NF training and not performing several MI-BCI sessions.

The experimental group participated in 3 NF sessions per week in one month. Each NF session started by recording 5 min resting state EEG in *relaxed with eyes-open* and *eyes-closed* condition. In total, 10 trials of 15 s were recorded in each condition according to the random visual cue provided on the screen. Subsequently, subjects played a game (See Fig. 2) for 20 min in which an avatar was moved along a path. The speed of the avatar was controlled by the subject. The subjects should keep being relaxed to increase their alpha rhythm and thus speed up the avatar movement. Finally, another 5 min resting state EEG data was recorded. In total, each NF session took around 30 min and the subjects were instructed to minimize their body limb movement during the whole experiment.

Each MI-BCI session comprised 2 non-feedback calibration runs and 2 feedback runs. During calibration runs, EEG



(a)



(b)

Fig. 1: The proposed experiment flow diagram for: (a) experimental group and (b) control group. The whole experiment took around 4 weeks for both groups.

Fig. 2: Experimental setup to collect EEG data during NF training sessions. Subjects should modulate their brain signals to move the avatar on the screen.

data were collected from subjects who performed right versus left hand kinesthetic MI. Each run contained 40 trials of each class, for a total of 160 trials, and a 2 min break was given after each run. Each trial of calibration run lasted about 12 s and contained a preparatory time segment of 2 s, followed by a visual cue for 4 s, and a 6 s rest period. Thus, each calibration run lasted about 16 min. The EEG data collected during calibration runs were used to train a model to detect MI in the two subsequent feedback runs.

During feedback runs, subjects performed MI of right versus left hand while receiving online visual feedback. Each feedback run consisted of 40 trials, and there was a 2 min break between the feedback runs. Each trial lasted about 16 to 18 s, a preparatory time segment of 2 s, followed by a visual cue for 4 s. After 1 s of online processing the type of MI task was then detected and a visual feedback was shown accordingly for about 3 to 5 s. Each feedback run lasted about 26 min. Similar to NF sessions, the subjects were instructed to minimize their body limb movement in BCI sessions. In order to reduce the effect of inter-session non-stationarity, each BCI session used different model trained based on calibration data collected on the same session.

B. EEG Signal Processing

In this experiment, EEG data from 25 channels were recorded using the Nuamps EEG acquisition hardware with unipolar Ag/AgCl electrodes, digitally sampled at 250 Hz with a resolution of 22 bits for voltage ranges of $\pm$ 130 mV and band-pass filtered from 0.05 to 40 Hz by the acquisition hardware.

The 2 min resting state EEG data in *eyes-open* condition collected prior each NF session was used to derive a spatial filter using spatio-spectral decomposition (SSD) [21]. The derived filter was subsequently used in an online NF training session. In fact, the SSD method extracted alpha rhythm with a more peaky spectral profile. In online NF sessions, every 200 ms the recently recorded 4 s of EEG measurements were spatially and then spectrally filtered over alpha band (8–13

Hz). The power of extracted alpha-SSD components was then calculated and scaled between 0 to 100 and shown as a brain score on the screen. The derived brain score determined the speed of the avatar.

In BCI sessions, the collected EEG data from calibration runs were processed using filter bank common spatial pattern (FBCSP) algorithm [22] to construct a subject-specific MI detection model. FBCSP band-pass filtered the EEG signal in 9 different bands between 4 Hz to 40 Hz. CSP was applied on the second stage to spatially filter the signal. Two pairs of features from each band were selected. Subsequently, the best 4 discriminative pairs of features were selected using mutual information and then fed into a linear discriminant analysis (LDA) classifier. The trained model was then used in online feedback runs. The output of the trained LDA classifier was continuously computed and shown as a feedback to the subjects. A happy (neutral) face was shown on the screen if the MI action was correctly (wrongly) detected.

III. Results

A. BCI performance results

Fig. 3(a) summarizes the feedback accuracies of 6 subjects from the experimental group before and after the 12 NF training sessions. As shown, the average feedback performance of the subjects in the first MI-BCI session was 56.77%$\pm$15.57 and the performance of the subjects varied from 46.25% to 87.5%. Only subject '*ab*' that had prior BCI experience had high accuracy 87.5% in the first BCI session and the rest of the subjects had performance below 70%, thus they were considered as poor performance subjects. The average feedback performances of the experimental group in the last MI-BCI session after 12 sessions of NF were considerably increased to 71.14%$\pm$16.62. We conducted a paired sample t-test to compare the feedback performances of the experimental group in the first and the last sessions. The results showed the performances in the last session were significantly higher upon the initial session p=0.02.

In order to evaluate the feasibility of our proposed design in addressing BCI deficiency, we excluded subject '*ab*' from our analysis and only compared the performance of the subjects with BCI deficiency. The results showed the average feedback performance of the 5 subjects with BCI deficiency improved from 50.63% to 67.75%. The results of paired sample t-test revealed the improvement was statistically significant p=0.018. Therefore, we can conclude that our proposed design successfully helped subjects with BCI deficiency.

Fig. 4 shows the EEG spatial patterns of subject '*gc*' who had significant performance improvement from the first to the last BCI session. The patterns corresponded to ERD and ERS for performing right and left hand MI. As shown, there was clear ERD/ ERS patterns in the last BCI session. This showed how well a subject with BCI deficiency learned to modulate his brain rhythms after several NF training sessions.

Fig. 3(b) shows the feedback performance of the control group in two BCI sessions. Two out of seven subjects had high feedback performance, while the rest had accuracy

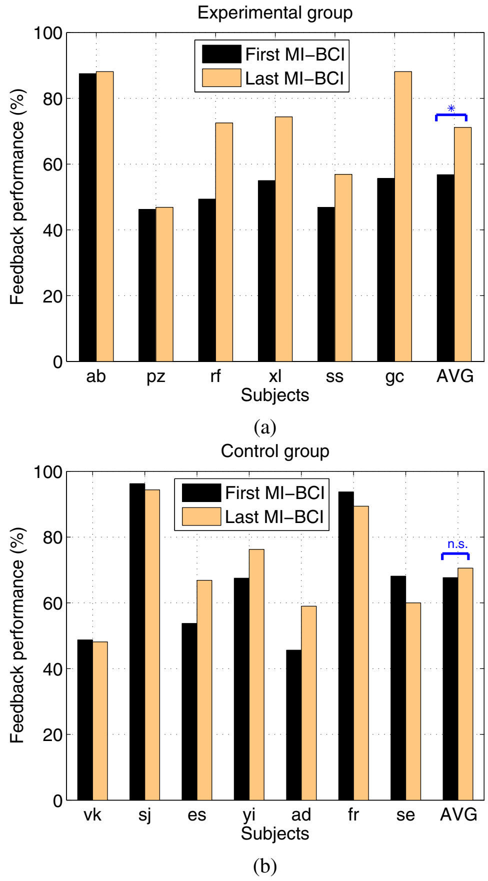


Fig. 3: The feedback performance (%) of (a) experimental group, and (b) control group in the first and the last MI-BCI sessions. (Paired sample t-test: * p<0.05; n.s. p>0.05).

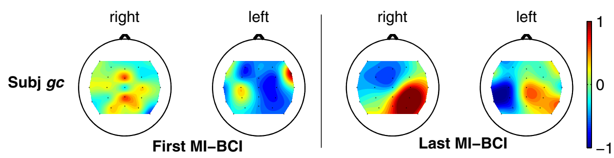
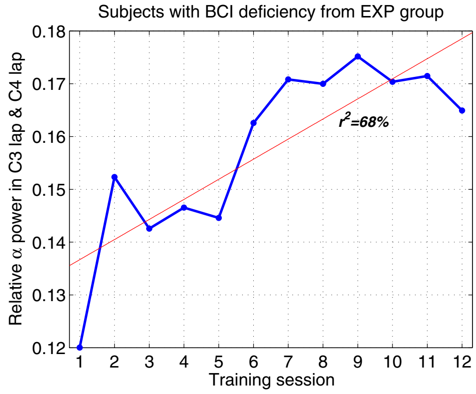


Fig. 4: The CSP patterns of subject *gc* in the first and the last MI-BCI session.

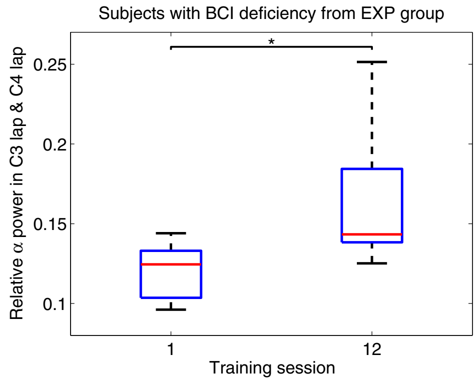
below 70% in their first BCI session. Similar to the experimental group, the control group also performed their final BCI session around one month after their first session. The average feedback performance of the control group showed slightly improvement, which was not statistically significant. The feedback performances of two high performance subjects '*sj*' and '*fr*' slightly deceased in the last BCI session but their performances were still above 89%. Although the average performance of the 5 subjects with BCI deficiency from the control group was increased from 56.75% to 62.05%, the improvement was not statistically significant p=0.14.

B. Neurofeedback results

The resting state alpha of subjects with BCI deficiency from experimental group over 12 training sessions is shown



(a)



(b)

Fig. 5: (a) Average relative resting state alpha power of subjects with BCI deficiency over 12 sessions. (b) Boxplot of relative alpha power in first and last training sessions. (Paired sample t-test *p<0.05).

in Fig. 5(a). Each dot represents the average relative resting state alpha activity in each NF session. The relative alpha power was calculated by dividing the alpha band power in the range 8–13 Hz by the broad-band power in the range 4–30 Hz. As can be seen, the resting state alpha activity increased over time. Fig. 5(b) revealed the results of paired sample t-test between the alpha power in the first and last training session. The alpha power in the $12th$ training session was significantly higher than the first training session p=0.04.

IV. Conclusion

In this paper, we proposed an approach to address BCI deficiency, which is one of the challenges in BCI applications. We hypothesized that by enhancing the resting state alpha rhythm, the MI-BCI performance can be improved. Therefore, we conducted an experiment to train the subjects increase their alpha rhythm in 12 NF sessions. Relaxation was a successful mental strategy to enhance the resting state alpha in NF sessions. The results showed the NF helped subjects to significantly improve their resting state alpha rhythms over the sensorimotor area, and helped subjects with BCI deficiency. This shows that the MI-BCI performance of the subjects can be improved by enhancing their resting state alpha rhythm. In conclusion, NF can be considered as a promising method to alleviate BCI deficiency of the subjects.

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