Performance of Motor Imagery Brain-Computer Interface Based on Anodal Transcranial Direct Current Stimulation Modulation

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Abstract—Voluntarily modulating neural activity plays a key role in brain-computer interface (BCI). In general, the self-regulated neural activation patterns are used in the current BCI systems involving the repetitive trainings with feedback for an attempt to achieve a high-quality control performance. With the limitation posed by the training procedure in most BCI studies, the present work aims to investigate whether directly modulating the neural activity by using an external method could facilitate the BCI control. We designed an experimental paradigm that combines anodal transcranial direct current stimulation (tDCS) with a motor imagery (MI)-based feedback EEG BCI system. Thirty-two young and healthy human subjects were randomly assigned to the real and sham stimulation groups to evaluate the effect of tDCS-induced EEG pattern changes on BCI classification accuracy. Results showed that the anodal tDCS obviously induces sensorimotor rhythm (SMR)-related event-related desynchronization (ERD) pattern changes in the upper-mu (10–14 Hz) and beta (14–26 Hz) rhythm components. Both the online and offline BCI classification results demonstrate that the enhancing ERD patterns could conditionally improve BCI performance. This pilot study suggests that the tDCS is a promising method to help the users to develop reliable BCI control strategy in a relatively short time.

Index Terms—Brain-computer interface (BCI), motor imagery, neuro-modulation, transcranial direct current stimulation (tDCS).

I. INTRODUCTION

Brain-computer interface (BCI) has broad applications in neural rehabilitation, user-state monitoring, communication and entertainment [1]–[4]. BCI is utilized to directly connect the human brain with the computer [3], [5] or neuroprosthetic [6] to replace the normal motor output pathway. Currently, most developed BCI systems are based mainly on the electroencephalography (EEG). Successful BCI classification and control involve an interacting dynamic process between the BCI system and the users. In the past few years, many lines of research focused on developing sophisticated pattern recognition and classification algorithms to decode reliable BCI control signal from noisy brain activity [7], [8], but the complexity of the algorithm challenged its applicability in real time. From the user side, although making trained feedback adapt to a BCI system is common [9]–[12], repetitive training increases fatigue and is not effective for all users. Hence, there is a growing interest to find out whether other techniques, such as neuro-modulation approaches, could promote the user ability to achieve an improved EEG BCI classification accuracy in a relatively short time.

In motor imagery (MI)-based BCI, the user learns to voluntarily modulate their sensorimotor rhythm (SMR) to control a BCI can be acquired in the same way as normal motor learning and skill acquisition [2], [13], [14]. Other studies indicate that noninvasive brain stimulation technologies, such as repetitive transcranial magnetic stimulation (rTMS) and transcranial direct current stimulation (tDCS), can modulate initial motor learning and consolidation [15]–[18]. tDCS is an effective and convenient method that induces polarity changes of a specific brain region by supplying weak direct currents to the head [19]. Such an action can modulate cortical excitability and activity without inducing neuronal action potential firing [20]. Furthermore, the effect of tDCS is not limited to a stimulation period but could last for one hour or more in the poststimulation period [21]. Recently, a study using animal brain slices demonstrated that the aftereffects of tDCS might be similar to long-term potentiation (LTP), which causes increased postsynaptic excitatory potentials [22].

Although the mechanism underlying tDCS induced ongoing-effects and aftereffects both remain controversial, a few human studies have demonstrated that anodal tDCS increases cortical excitability over primary motor cortex (M1) which plan and execute movements associated with other motor areas [19], [21], and two recent studies reported that this effect could enhance motor skill acquisition ability [23] and alter generalization patterns of motor learning [24], [25]. Based on these findings, the possibility of an enhancement of movement, which is related cortical activation by tDCS on motor cortex, can be reasonably considered. To the knowledge of the authors, only one study indicated the ability of tDCS stimulation on M1 to modulate SMR event-related desynchronization (ERD) during MI [26] until recently. In considering an MI-based BCI system, the EEG signal is no longer limited to an observation for inspecting the neural...
oscillation and synchrony activities inside the brain. It becomes the signal for representing the voluntary movement intention of users, which is utilized to control outside devices. If tDCS can modulate motor cortical excitability and induce the consistent EEG activity during movement execution and imagination, the question is whether the EEG pattern alteration caused by tDCS can improve the classification performance of an MI-based BCI system.

In this study, an experiment paradigm that combines anodal tDCS stimulation with EEG recording to identify the SMR pattern changes induced by anodal tDCS during imagination movement in a cursor-movement-feedback BCI system is designed. Moreover, the effect of these pattern changes on BCI classification performance is evaluated. The difference of BCI performance with several offline decoding methods is assessed, and which type of the BCI system is more suitable to be combined with anodal tDCS stimulation is indicated. To evaluate the possible effect of tDCS on SMR, two sequential BCI feedback sessions would be conducted for each subject in the study. The first session was done prior to tDCS stimulation, and the second session was immediately done following a tDCS-stimulation session. The influence of the tDCS stimulation on SMR then could be measured by the ERD pattern difference between the two sessions. The experiment was conducted and completed within one day for each subject, and the result reflected the short-term effect of anodal tDCS stimulation. The subjects were randomly divided into four subgroups to validate the true stimulation effect versus sham stimulus and the impact of anodal tDCS on different cortex region for different hand MI tasks.

II. METHODS AND MATERIALS

A. Participants

Thirty-two right-handed-dominant and healthy participants who are free of medication, alcohol, and any nervous and mental problem experience were recruited for the research. All the participants were compensated for their participation. The participants are adult males aged between 22 and 28 years [26.3 ± 1.97 (mean ± std. years)]. All the participants read, filled up and submitted an informed consent form (ICF) before commencement of the experiment. Ethical approval has been secured from the human ethics committee at Shenzhen Institutes of Advanced Technology, Chinese Academy of Science. All participants were naïve to BCI control and were randomly divided into four subgroups: 1) right hemisphere anodal stimulation group (RA); 2) right hemisphere sham stimulation group (RS); 3) left hemisphere anodal stimulation group (LA); and 4) left hemisphere sham stimulation group (LS). Each subgroup had eight subjects. The experimental procedure complied with the declaration of Helsinki (World Medical Organization).

B. EEG Acquisition and System Design

Twenty-one Ag/AgCl electrodes over the M1 and the supplementary motor cortex (SMA) were selected. The ground electrode was mounted at the forehead, and the reference electrode was selected between the Cz and CPz. The layout of 21 channel locations was done following the international 10–20 system with a regular inter-electrode distance of approximately 2.5 cm (Fig. 1). The monopolar EEG signals from the Ag/AgCl electrodes were acquired using a SynAmps2 amplifier (Neuroscan USA) with the sampling rate at 1000 Hz. The electrode impedance was kept below 5 kΩ. A band-pass filter between 0.05 to 200 Hz and a 50 Hz notch filter were applied to the EEG recordings. Scalp EEG recordings were fed into BCI2000 software for processing and analysis [27]. The standard cursor control task in BCI2000 was used in the experiment and the online BCI algorithm is the default one in BCI2000. Subject-specific control signal channels and frequency were initialized during the training session [28] (Table I). The raw EEG recordings were digitally filtered through a common average referencing (CAR) spatial filter to further increase the signal-to-noise ratio. Autoregressive (AR) spectral power of the signal in subject-specified channels and frequency bins were calculated in a 500-ms window with a time increment.

Fig. 1. Design of the experiment. (a) Layout of the recording electrodes and the anodal tDCS stimulation electrodes placement in the RA group. (b) Procedure of online experiment paradigm and BCI system. (c) Illustration of online paradigm of motor imagery. (d) Block diagram of EEG processing for different processing stages.
of 40 ms (460-ms time overlapping). The control signal was generated by subtracting the AR power between the two EEG electrodes for every 40 ms. The control signal was used to move the cursor up/down to hit a target.

C. Transcranial Direct Current Stimulation

The weak direct current was administered by the Phoresor II Auto (Model PM850, IOMED, Salt Lake City, UT, USA) using two rectangular saline soaked sponge electrodes (35 cm$^2$). A constant current of 1 mA intensity was applied for 15 minutes. An anodal electrode was placed over the left (LA, LS) or right (RA, RS) side of the M1 according to different groups. The exact position of anodal electrode for each subject was identical with the optimized individualized electrode location at the same side of the hemisphere (Table I), which was specified in the BCI2000 initialization session. The cathodal electrode was placed over the contra-lateral supraorbital area. For all four groups of subjects, the anodal current was in a fade-in and fade-out phase (10 s increasing the current intensity to 1 mA, 10 s decreasing the current intensity to zero) at the beginning and end of the stimulation. For the anodal stimulation groups, the current was kept constant during the stimulation period. For sham stimulation groups, the current was conducted for 30 s to mimic the sensation at the beginning of the anodal stimulation (10 s fade-in to 1 mA, 10 s constant in 1 mA and 10 s fade-out to zeros). Most subjects perceived the stimulation as a kind of itching sensation under the location of stimulation electrode [29]. All the subjects were blinded to which kind of stimulation they were undergoing, and most of them only felt the sensation at the beginning of the stimulation. Therefore, the experiment was a single-blind, within-subjects, sham-controlled study.

D. BCI System Design and Online Experimental Paradigm

The duration of one trial was 8 s with 4-s feedback periods. At the first second, a red rectangle was presented on the screen of a computer monitor that was placed in front of the subject, indicating the beginning of a trial. At the third second, a red small ball appeared and began a movement to the right edge at a constant speed. The subject was instructed to perform the task according to the position of the rectangle. A top right rectangle indicated a right-hand MI task, and a bottom right rectangle indicated a left-hand MI task. There was a 1-s gap between two trials, and the subject was asked to relax during that interval. Subjects were told to imagine clenching their fist when they were performing the task. To suppress the electrooculogram (EOG) and electromyography (EMG) artifacts, subjects were asked not to blink their eyes or move their body during performance. The experiment included two sessions, and each session had seven runs. Each run was composed of 20 trials that were randomly divided into two classes, namely right-hand and left-hand classes, with an equal number of trials. Therefore, the dataset of one session consisted of 140 trials and 70 trials per class. A session was completed within 30 minutes.

After the first online BCI session, anodal tDCS stimulation was administered to the subjects according to their groups. To keep the position of the electrode unchanged between the pre- and post-stimulation session and shorten the electrode replacement time, the electrode cap containing 23 electrodes were designed, and two interstices in both sides of the electrode cap, which could be opened and closed by two plastic zippers, were simultaneously made. During the online BCI experiment, these zippers were fastened. During the tDCS-stimulation phase, the electrode cap was disconnected from the amplifier, and the specified side of the plastic zippers was unfastened so that anodal electrode could be placed under the specified recording electrode through the interstices. The center of anodal electrode was placed exactly at the position of the subject-specific control electrode in corresponding hemisphere. Simultaneously, a cathodal electrode was placed over the contralateral supraorbital area. The anodal and cathodal electrode could tightly touch the scalp by the elasticity of the electrode cap. After the stimulation,
the position of the electrode could be kept almost unchanged as the electrode cap had not been removed during the stimulation. Therefore, the effect of anodal tDCS could be measured in time, and the almost identical position between the pre- and post-stimulation session would more accurately reflect the effect of anodal tDCS in the stimulation position. After the tDCS phase, the subjects underwent the second session of BCI experiment. The frequency bands, electrode locations, and adaptation values were customized in a manner similar to that at the beginning of the first session. Thus, the conclusion of the study was irrelevant to the parameter setting of the BCI system. All data were saved for following offline analysis. The online experimental paradigm is shown in Fig. 1(a)–(c).

E. ERD/ERS Quantification and Comparison

All the trials were visually assessed excluding the artifacts caused by eye or body movement. The total number of trials in each session for one subject was kept at no less than 120. The EEG signal recordings were digitally down-sampled to 100 Hz and underwent a 5–40 Hz band-pass filter. All channels were re-referenced using a CAR spatial filter for the following analysis. To evaluate the possible EEG pattern changes caused by anodal tDCS, the individual spatial and spectral ERD/ERS in the pre- and post-stimulation phase, respectively, were calculated. However, the common effects may not easily be identified from the pre- and post-stimulation comparison for each subject because some individual unpredictable factors, such as online self-adaption, fatigue, or lack of attention during the task, may disturb the objective observation. Hence, the results for subjects within the same group were averaged to suppress the within-subjects interference. The effect of anodal tDCS could be distinguished by comparing the group mean values.

The ERD/ERS value was calculated from the mean band power in three separated EEG rhythm bands [lower-mu (8–10 Hz), upper-mu (10–14 Hz), and beta (14–26 Hz)] during feedback. The baseline value was the mean band power of 0.5–1 s before cue onset and 0.5–1 s after feedback. These data were used to map the ERD/ERS topography. The right-tailed, two-sample t-test was performed between pre- and post-stimulation was defined by (5) and (6) where a positive value means an increase in these values.

The ERD/ERS value among these four groups was difficult. Instead, the spectral-temporal ERD/ERS value is calculated as [31]

\[
ERD(t, f) = \left[ \frac{(F(t, f) - R(f))}{R(f)} \right] \times 100 \%
\]

where \( F(t, f) \) indicated the spectral power during the feedback period and \( R(f) \) is the averaged power of the reference period which is 0.5–1 s before cue onset and 0.5–1 s after feedback [32]. Since the traditional ERD/ERS calculated method is hard to describe, the ERD/ERS simultaneously increases and decreases. Therefore, in this study, the original ERD/ERS difference spectral was divided into two independent ERD and ERS difference spectral. ERD/ERS value for each subject in each channel was separately calculated using the following formula:

\[
VERD(t, f) = \begin{cases} 
ERD(t, f) & \text{if } \text{ERD}(t, f) < -\text{threshold} \\
0 & \text{if } \text{ERD}(t, f) \geq \text{threshold}
\end{cases}
\]

\[
VERS(t, f) = \begin{cases} 
ERD(t, f) & \text{if } \text{ERD}(t, f) > \text{threshold} \\
0 & \text{if } \text{ERD}(t, f) \leq \text{threshold}
\end{cases}
\]

In statistical analysis, data were the ERD/ERS value changes rather than the original ERD value. The two-way analysis of variance (ANOVA) was used to compare the ERD changes with the main factors of “group” (active, sham) and “task” (left, right). If the ANOVA manifested a significant difference (\( p < 0.05 \)), a post hoc Fisher’s least significant difference (LSD) analysis was carried out. Moreover, because the area of the stimulation electrode is opposite between the two of paired groups (RA, RS versus LA, LS) and because the local SMR activation patterns are distinguishable, directly comparing the ERD/ERS value among these four groups was difficult. Instead, RA and LA were only compared with their control groups RS and LS, respectively.

F. BCI Performance Evaluation

To investigate whether anodal tDCS can facilitate the online BCI control, the online hits rate (HR), which is a performance index reported by BCI2000, was used to directly evaluate the online controlling ability change of the subjects. Hit rate is the ratio of the number of the successfully targeted hits during trials to the total number of trials. The HRs for different classes were separately calculated.

Because HR is a coarse index for evaluating BCI performance, in the offline study, the classification accuracy (CA) by different classification methods on offline EEG dataset was used for further comparison. To evaluate which types of BCI feature extraction and classification algorithms could be benefited
from the anodal tDCS stimulation, four different combinations of popular BCI signal processing algorithms were introduced as follows.

1) AR+MDBLC: Two channels’ autoregressive (AR) power of optimized frequency bands was selected as the features and a mahalanobis distance-based linear classifier (MDBLC) was applied to classify MI task. This combination simulates the signal processing default in BCI2000.

2) CSP+MDBLC: Two channels’ AR power cannot fully capture the valuable spatial information. Thus a popular BCI spatial feature extraction algorithm, called common spatial pattern (CSP) [33], was utilized to construct spatial filters and to maximize the variance of multichannel EEG signal between different mental classes. The first spatial filter was selected, and the variances of the first and last rows of the projected signal were extracted as features.

3) CSP+LSVM: The information on class difference may not only be contained in the first and last rows of the CSP spatial filtered signal. Following a standard parameter setup of the method, the first three spatial filters by CSP were selected, and the variances of the first three and last three rows of the projected signals were used. However, the increasing dimension of the feature space caused by using this setup is needed to introduce more robustness classifier to handle. Thus a linear support vector machine (LSVM) classifier was applied in this study.

4) FBBCSP+LSVM: The effectiveness of CSP highly relies on prefiltering EEG signal into the specific frequency bands, which are mostly related to MI intention. Several improved CSP algorithms have been proposed to optimally select the subject-specific bands. A filter bank CSP (FBBCSP) method was used: the EEG signal was first filtered into mu and beta frequency bands, and the same procedure was separately applied on the two bands signal as in method 3). With accuracy of final classification, the best result between the two bands was selected.

A block diagram of EEG processing for different processing stages was shown in Fig. 1(d). Before offline processing, the signal was band-pass filtered between 7–30 Hz, and only the SMR rhythm components were kept. An epoch signal of 0.5–1.5 s after the feedback started was labeled as the “left”/“right” class, and another epoch of 0.5–1 s before cue onset and 0.5–1 s after feedback period was labeled as the “rest” class. The left-rest and right-rest task classification performances, instead of the left-right task classification, were measured. The reason for using this offline simulation classification paradigm is explained in the succeeding section. Leave-one-out cross validation was carried out to access the mean classification result from the total seven runs in each session, six runs were used to training and the left one run to test. This procedure is carried out seven times and the final result is the mean of the seven classification accuracies.

III. RESULTS

A. Effect of Anodal tDCS on Spatial and Spectral EEG Activation Patterns

Spatio-temporal ERD/ERS patterns at somatotopically selected electrode locations are responsible for identifying different types of motor intend. Fig. 2(a) and (b) shows the group average of task-specific ERD/ERS topographies during the pre- and post-stimulation sessions in the different bands. In Fig. 2(a), the most remarkable change was found in RA: for the left-hand task, the contralateral ERD in the upper-mu at FC4, C4, C6, CP4 and CP6, and in the beta at C4 and CPz were significantly strengthened; for the right-hand task, the ipsilateral ERS on the stimulating side was slightly lower, and, interestingly, the contralateral ERD both in the upper-mu and the beta at C3, which were away from the stimulating side, also were strengthened. In the opposite ends, the results of RS showed no obvious change between sessions in the upper-mu and the beta. In Fig. 2(b), the clear increase in ERD was mostly found in LA for the right-hand task, which was located at FCz, FC2, C3, C1, Cz, C2, and CP1 in the beta. Similarly to RS, no obvious change between sessions was found in LS. In addition, the lower-mu did not change between sessions either in which factor for task (left, right) or stimulation (active, sham).

The spectral-temporal ERD/ERS change under stimulation condition was described. Whereas the topography results showed that the effect not restricted to the stimulation location and several adjacent channels showed different levels of effects, for a fair comparison, the only selected channel was under the center of the anodal rectangular pad, and the following analysis all followed the same criterion. In Fig. 3(a), RA for the left-hand task had a clearly contralateral ERD increase after stimulation in the mu and wide range of the beta during the MI period. The ERD difference spectral showed that the most obvious increase was close to the upper-mu (10–14 Hz) and the beta (15–30 Hz); for the right-hand task, the ipsilateral ERD only in the center band of beta (20–25 Hz) slightly increased. In contrast, the ERD differences spectral of RS showed no obvious change in either condition. In Fig. 3(b), the averaged contralateral ERD of LA in mu (12–14 Hz) and beta (15–23 Hz) during feedback period also largely increased in the post session. The ipsilateral ERD increase was found in the beta (15–23 Hz) with lower extent. Otherwise, in LS, a clear ERS increase in the mu rhythm for both tasks was shown. This phenomenon was considered the natural pattern of development during sessions [34] and could become a potential interference factor in this study.

B. Statistics Analysis on ERD/ERS

In Fig. 4, the two-way ANOVA was performed on ERD/ERS change difference within the divided bands using the variables “group” (RA, RS, LA and LS) and “task” (left-hand task and right-hand task): between the paired group RA and RS, a significant interaction between whether to deliver the stimulation and the type of task (Group × Task) was found in the upper-mu band [F*(1,28) = 5.53, p = 0.026]. Post hoc LSD analysis showed a statistically significant ERD increase in RA for the left-hand task compared with the right-hand task (p = 0.01), and with RS for left-hand task (p = 0.003) (see Fig. 4). The same significant interaction in the upper-mu was found between the paired group LA and LS [F*(1,28) = 4.21, p = 0.049]. Post hoc LSD analysis showed that the ERD significantly increased in LA for the right-hand task compared with that for left-hand task (p = 0.023), and with LS for the right-hand task.
These results suggested that tDCS can enhance the upper-mu ERD when performing MI tasks. Furthermore, the ERD increasing effect of anodal tDCS is not an additive but an interaction result of the stimulation and the type of task. In other words, the stimulation effect is more significant during the period when the subject performs the stimulation contra-lateral hand task (left-hand task for RA, right-hand task for LA). Moreover, it failed to reveal significant interaction in the lower-mu and in the beta band. In the beta band, between the paired group RA and RS, a significant main effect was found with factor of group [$F^{**} (1, 28) = 9.502, p = 0.005$]). A two-sample t-test showed a significant ERD increase in RA compared with RS for the left-hand task ($p = 0.021$). Meanwhile, a two-sample t-test exhibited a significant ERD increase in LA compared with LS ($p = 0.034$) for the right-hand task (Fig. 4). Firstly, these results confirmed that anodal tDCS could not induce the ERD change in the lower-mu. Secondly, anodal tDCS can enhance the beta ERD. However, because only a significant main effect was found and there is no significant interaction between the group and task, it indicates that the increased effect is not restricted to specific hand tasks. The reason might be that the phenomenon of beta ERD is not limited to the contra-lateral hand task as the ERD phenomenon in the upper-mu.

In addition, there is no difference of the mean reference power between sessions for each group. This means that anodal tDCS does not affect the MI free oscillatory activity. Moreover, the comparison between the stimulation positions (RA, LA) showed no significantly different level, indicating that the effect of tDCS
Fig. 3. Averaged ERD values and difference of ERD/ERS between two sessions. (a) RA and RS group, (b) LA and LS group. Channels are selected as the position under the center of the anodal. The first two columns manifest the ERD values. Last two columns separately indicate the difference of ERD and ERS between pre- and post-stimulations. Dashed line at second two denotes the start of the MI tasks. Gray area denotes the rest periods that used for the baseline.

on either dominance or non-dominance hand representation area may not be different, at least with the short-term effect (data not shown).

C. Online BCI Performance

Because the major goal of the study is to figure out the short-term effect of anodal tDCS on BCI classification, we focused on comparing the significant differences of classification performance between the pre- and the post-stimulation session. For a fair comparison, all the subjects are naïve to BCI and there is no any training procedure before the experiment. Comparing the online hit rate change, seven subjects in RA reached higher HRs during the post session for the left-hand task [Fig. 5(a)]. The average increases in HR of RA for left-hand and right-hand tasks were 3.75 + 4.38 and 4.64 + 8.96 (mean ± std.%), respectively. The average changes in HR of RS were 0.55 + 7.06 and 0.59 + 10.06. Based on the comparison of the results between LA and LS, although the post-session ERD for the right-hand task was strengthened in the LA group, the post-session right-hand task average HR changes of LA and LS were
Fig. 4. Statistic analysis of the ERD difference of the pre- and post-stimulations. The average value with the standard error was presented, and the individual subject information is illustrated by different symbols. Rows represent the different groups, and columns represent the different band. Significant levels are indicated by the asterisk ($p^* < .05, p^{**} < 0.01$) (in the upper mu band post hoc LSD manifests: $p^{**} = 0.003$ between RA versus RS for left-hand task, $p^* = 0.01$ between left-hand versus right-hand task in RA, $p = 0.015$ between LA versus LS for right-hand task, $p^* = 0.023$ between left-hand versus right-hand task in LA; beta band two-sample t-test: $p^* = 0.021$ between left-hand versus right-hand task in RA, $p^* = 0.034$ between left-hand versus right-hand task in LA).

The online BCI performance was assessed using the ANOVA with factors for time (pre, post) $\times$ hand (left, right) $\times$ stimulation (active, sham). However, there was no significant difference in the online BCI performance of the interaction.

D. Offline Simulation Classification Results

Not all the subjects in real stimulation groups showed the expected improvement in performance during online testing. A possible reason is that the anodal tDCS may induce localized ERD increase in both tasks and weaken the pattern separability in some cases. In order to evaluate the impact of anodal tDCS on the unilateral hand motor imagery BCI task, the binary classification between left-hand and right-hand task was replaced by the classifications of left (right)-hand task and rest. Firstly, by utilizing the combination of AR+MDBLC, which simply simulated the default BCI2000 signal processing, all of subjects in RA reached higher CA in post session for left-rest task [Fig. 5(b)]. The averaged CA change of left-rest task in RA with $8.53 \pm 8.04$ was significantly higher than RS with $-2.58\pm7.00$ (Table II). Meanwhile, in LA, CA for right-rest task of all subjects also increased [Fig. 5(b)]. Moreover, the averaged CA change of right-rest task in LA with $7.89 \pm 5.29$ also was significantly higher than LS with $1.83\pm10.04$ (Table II). In addition, the differences of the average CA change of right-rest task between RA and RS, and left-rest task between LA and LS were both insignificant. However, the overall BCI performances under this combination of methods were low (mean below than 60%). Hence, CSP was introduced to extract information from all recording channels (combination 2). However, along with the increasing dimensionalities of the feature space and limited number of training samples, the MDBLC cannot produce a good result (Table II). Combining CSP with LSVM (combination 3) slightly enhanced the overall performances, but original CSP filter is less able to extract the spectral-temporal information, and the effect of tDCS on specific frequencies could drown in the wide range signal (Table II). Thus, the FBCSP was used to select the subject-specific frequency within CSP. The result of the combination of FBCSP+LSVM showed the highest CA (mean about 75%). All subjects in RA reached higher CA in the post session for the left-rest task [Fig. 5(c)]. The average CA change of the right-rest task in RA was $4.82 \pm 3.70$ compared to RS with $-0.65\pm9.91$ (Table II). However, the CA change of right-rest task in LA did not show a significant increase. This is partly due to observation that one subject ([la05] (Fig. 5(c)) in LA clearly showed a 10% decline in performance during the post session.

IV. DISCUSSION

A. Effect of Anodal tDCS on ERD Patterns and MI Based BCI Classification

The evolution of neural pattern for controlling BCI is generally viewed to mostly depend on repetitive training, through which the user develops his/her own control strategy by self-regulation. The noninvasive brain stimulation technique may provide an alternative way to modify neural pattern. Matsumoto et al. [26] indicate that tDCS could modulate the ERD during MI. In the current study, data demonstrated a few more interesting findings: 1) anodal tDCS can induce both the upper-mu and the beta ERD increase; 2) anodal tDCS only enhances the ERD and does not induce an increase in ERS or a change in resting EEG potentials; 3) anodal tDCS mostly induces the localized ERD increase but does not restrict to the center of the stimulation location; 4) anodal tDCS induces the ERD increase for both MI tasks, but the increased level is determined through the interaction between the stimulation and the MI task type.
These findings will contribute to the development of a more favorable control signal. First, many studies have shown a functional dissociation between the upper and the lower-mu rhythms [35]. Particularly, the upper-mu ERD shows a somatotopically specific pattern of motor type. This component is stable across sessions and does not differ whether feedback existed or not [34]. Interestingly, at least in the current study, tDCS is found to directly modulate SMR-related ERD, especially in the upper-mu band. The effect of tDCS may enhance the SMR-related ERD discriminability between the different MI patterns. Furthermore, the ERD change for the sham stimulation groups was found to be insignificant. Second, anodal tDCS can enlarge the difference between activation and resting EEG pattern by amplifying the power that decreased during MI. This characteristic may help elicit the special mental task from the baseline EEG. Third, a pilot modeling study by Datta et al. [36] demonstrate that the spatial resolution of conventional tDCS was relatively diffused and could result in unfocal modulation over the widespread cortical surface. The result of this study partially fits this model. The ERD increase may not be restricted to the stimulation center, especially of the beta oscillatory network. However, to conclude from the current information whether other areas far from the stimulation location can be influenced by the direct or indirect effect due to tDCS is difficult. Thus there is a tradeoff between the stimulation effectiveness of anodal tDCS and the recording channel map selection for BCI control. On the one hand, the fewer recording channels that nearby the stimulation position are selected, the more focalized effect of anodal tDCS can be achieved, but the overall BCI performance will be limited due to the lower spatial resolution. On the other hand, BCI can exhibit more powerful classification ability with more channels, but the positive effect of anodal tDCS might be smeared by the muffled pattern causing by other noneffects channels. Fourth, anodal tDCS led to more desynchronization activity in both tasks, but the level of ERD increase for stimulation contralateral side hand task is often larger than stimulation ipsilateral side. Based on an overall consideration, in most cases, anodal tDCS enlarges...
the relative ERD/ERS pattern difference between two tasks. In other fewer cases, however, after stimulation, a standard focal ERD/ERS pattern may change into the bilaterally ERD in whatever task, and anodal tDCS provides limited performance enhancement under this condition.

### B. Anodal tDCS Contributes Which Type of BCI Classification

Results of this study indicate that anodal tDCS play major role in making the task-specific brain activation pattern more distinguishable between different classes. Nevertheless, in online testing, not all subjects in real stimulation groups showed improvement in post-stimulation performance corresponding with the change in certain ERD/ERS activation. As mentioned earlier, this can be partly attributed to the reduction of the relative ERD/ERS pattern difference between classes in special cases. In comparison of the offline classification, the two-class classification was modified to the one-class detection problem. Under this situation, if only one channel at stimulation ipsilateral side was selected to detect hand task of contralateral side, the post-stimulation CA stably increased for all the subjects in both two real stimulation groups. However, if more channels’ information included in different brain region activities was involved in BCI classification, the positive effect of anodal tDCS on BCI classification may be weakened by other unpredicted changes on noninfluenced channels of tDCS.

Recently, the Graz BCI group developed a new asynchronous BCI that uses a single channel to detect the foot MI [37]. Under this paradigm, the performance could be possibly enhanced through tDCS. One challenge to achieve this goal is to select other proper features rather than use the short-lasting post-imagery beta ERS rebound. This is because this feature does not show positive change by anodal tDCS. Based on the findings, either translating the control signal to ERD pattern or changing the stimulation polarity could be the possible solution.

### C. Alternative Feedback or a Direct Modulation?

Training with feedback seems crucial for BCI learning following the classical motor learning theory. Thus it seems plausible to believe that the feedback has the ability of guiding a more pronounced event-related neural activity. Neuper et al. [34] report that a significant ERD increase was revealed between with or without feedback. A very striking result, however, was that the feedback-induced ERD increase is particularly found in the lower-mu and beta, and the upper-mu ERD showed no difference either with abstract/realistic or without feedback. The cortical activity during motor learning with feedback inevitably involves complex mechanisms of the sensory-motor integration. The upper-mu component may represent an intrinsic property of cortical activity, which is related only to motor execution or motor planning and is independent of any sensory feedback. In this study, the ERD activation pattern of upper-mu and beta can be strengthened through anodal tDCS between sessions. Based on the hypothesis of mu rhythm functional dissociation, the role of anodal tDCS may not be an alternative feedback that attempts to provide the sensory input into the cortex but a more direct way to modulate some intrinsic motor function and facilitate the user to generate clearer task-specific activation pattern for BCI control.

### D. Conclusion and Prospect

Considering all the facts in this study, a conclusion is that the combination of the anodal tDCS with MI-based BCI protocol effectively modulates the specific components of SMR-related ERD activation pattern during motor imagery and conditionally contributes to the improvement of ERD-dependent BCI classification performance. Findings of this study suggest that anodal tDCS could provide the short-term enhancement effect on BCI classification, and this effect may partially be attributed to the feedback-free EEG component.
A prospect of BCI is to benefit the patients who completely or partially lost their motor ability. However, Hill et al. [38] propose that due to long-term physiological changes caused by a disease, chronic paralysis for example, patients may hardly modulate their SMR and seem impossible to perform an MI task with a self-regulated SMR to control a BCI. If self-regulation ability is absent, whether the noninvasive stimulation can trigger the functional cortical activation is unknown. The pilot results for the healthy subjects show that the effect of anodal tDCS on learning to control BCI for disabled patients is worthy of study.

Furthermore, both BCI and tDCS techniques can be generalized as parts of neuro-modulation technology. For example, people can learn to control a BCI with neuro-feedback involving active self-regulation of the neural activity, and the neural activation pattern also can be passively altered through tDCS neuroactive self-regulation of the neural activity, and the neural activity is absent, whether the noninvasive stimulation can trigger the functional cortical activation is unknown. The pilot results for the healthy subjects show that the effect of anodal tDCS on learning to control BCI for disabled patients is worthy of study.

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References


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