Transcranial Direct-Current Stimulation Effect on a Speech-Imagery-based BCI

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Abstract— **Transcranial direct current stimulation (tDCS) is a neuromodulation technique that applies a small electrical current to a user's scalp to stimulate the brain. This preliminary study is conducted to examine the effect of tDCS to the performance of a speech-imagery-based brain-computer interface (SI-based BCI) system. SI-based BCI experiments were conducted on six participants where three participants receive tDCS and the other three receive sham-stimulation. The comparison between the accuracy of pre-stimulation and post-stimulation sessions of tDCS and sham-stimulation group suggests that a tDCS can slightly boosts the performance of a SI-based BCI system. However, the experiment is needed to be repeated on a greater number of participants to confirm the theory.**

Keywords—BCI, EEG, speech-imagery, tDCS

I. INTRODUCTION

Brain-computer interface (BCI) is a technique that translates users' brain activities into computer commands [1]. It is originally invented to help paralysis patients such as those who suffer from amyotrophic lateral sclerosis (ALS) to regain their abilities to communicate with the environment. BCIs can be categorized based on how and which type of mental tasks are given to the user. In an active BCI system, a user intentionally performs a specific mental task and the corresponding brain activity is extracted by the system to derive an output command. BCIs that are based on motor-imagery (MI), a mental task that lets a person imagine body movements without actually perform the movements, is one example of the active BCI. It has been shown in many previous researches that MI-based BCIs are effective in helping users to control external devices such as an electric wheelchair or a robotic arm with high accuracy [2][3]. Similar to the MI-based BCI, speech-imagery-based BCIs utilize speech-imagery (SI) tasks to generate specific brain activities for the system to detect. SI refers to a mental task where a person speaks inside their head without producing any actual sound or movements [4]. SI-based BCIs have advantages over the MI-based BCIs. First, SI tasks are easier to perform because of their intuitiveness whereas MI task requires some training to get familiar with. Second, it is more convenient in terms of the system design since we can easily match the meaning of the words in the SI task (e.g., imagine speaking the word "On") to the actual output command (e.g., turn on the TV). Last, SI-based BCIs also, in theory, allow as many commands as there are words, while MI-based BCIs are limited by the number of body parts for the MI tasks. Although early SI-based BCI researches focus on brain activity from electrocorticography (ECoG) during SI tasks [5], recent studies have shown that SI can be detected efficiently using non-invasive electroencephalography (EEG) as well [6].

Transcranial direct current stimulation (tDCS) is one of the noninvasive neuromodulatory techniques that applies a small electrical current to the scalp in order to stimulate a person's brain [7]. Although the exact mechanisms of how tDCS stimulate the brain are not yet to be fully understood, it is thought that the small current from tDCS may alter the electrical environment of cortical neurons that leads to the increase of their excitability which could enhance the brain's functionality. Depending on the polarity of the electrodes used for the stimulation, tDCS can induce a temporary effect similar to the long-term potential (LTP) or long-term depression (LTD) plasticity state, which then "up-modulate" or "down-modulate" the part of the brain being stimulated. Previous studies have demonstrated several effects when tDCS is applied to a different part of the brain. For example, the study in [8] and [9] applied tDCS with an anodal electrode on the left dorsolateral prefrontal cortex (dlPFC) which is part of the brain that is responsible for human selective attention. The results from these studies showed that performing tDCS on this brain area can enhance a user's ability to sustain attention to a task and increase the performance on behavioral tasks designed to measure the user's attention level. In contrast, the study in [10] applied tDCS on the left dlPFC using a cathodal electrode and found that this opposite setup of the tDCS can help participants to relax the previously-learned constraints on a task. In other words, it can boost a user's creativity in order to solve a specific problem.

Some previous studies have also examined the effect of tDCS in the field of BCI research as well. The study in [11] and [12] performed tDCS using an anodal electrode on the sensorimotor and motor cortex and a cathodal electrode on the left side of participants' forehead and investigate its effect on a MI-based BCI system. The result from these studies shows that tDCS can increase participants' performance on a MI-based BCI system in terms of accuracy when compared to the participants who receive sham stimulation.

This current study serves as a preliminary study on the effect of tDCS on the performance of a SI-based BCI system. We believe that tDCS can also boost the performance of SI-based BCI systems in the same way it did for the MI-based ones. In this study, we applied tDCS using an anodal electrode on the participants' left forehead and a cathodal electrode on the back of the participants' neck. We conduct SI-based BCI experiments on six subjects in three-conditions: pre-stimulation, tDCS-stimulation, and sham-stimulation, and compare the results of the experiments among three conditions. The method of how SI features are detected and the experimental procedure are described in the next section.

II. Method

A. Participants

Six male participants are recruited for this study. Participants are 25-29 years of age and fluent in English. All participants were healthy and free from any neurological disorders. All subjects have prior experience in BCI but they have never experienced tDCS or any kind of neural stimulations before. All participants gave written informed consent.

B. Transcranial direct current stimulation

Two types of stimulation: tDCS-stimulation and sham-stimulation are used in this study. During the tDCS-stimulation session, electrical current is delivered at 2mA continuously for the whole session, whereas the same electrical current is delivered only for 1 minute and automatically turned off in the sham-stimulation session. The battery-powered tDCS tool is controlled wirelessly using WeMos D1 mini wifi board and a relay module. Reusable transcutaneous electrical nerve stimulation (TENS) unit pads are used as the electrodes for tDCS. The electrodes are 2×2 inches in size. SI is thought to be highly correlated with the brain area in the left hemisphere, and the boost in the user's attention level could possibly benefit the participants' performance in SI-based BCI system. Thus, we attached the anodal electrodes at the area between the left side of the participants' forehead and the left temple and attached the cathodal electrode at the back of the participant's neck (figure 1). This tDCS setup lets the electrical current run through and stimulate the left-hemisphere.

C. EEG acquisition

EEG is acquired in 32 channels using BrainVision actiCHamp with an EEG cap. The sampling rate was 500 Hz. The EEG electrodes are placed around the left-hemisphere according to the 10-20 international system (figure 2). The EEG signals are referenced and grounded to the Fpz and FCz channels, respectively. The electrodes are placed only on the left hemisphere to increase its coverage on the brain area associated with SI, especially in Broca's area (F5, FT7, FC5, and FC3) and Wernicke's area (TP7, CP5, CP3, and P5). We insert electrolyte gel in the EEG cap to ensure the low impedance level and the connections between electrodes and the participants' scalp. The equipment preparation time takes approximately 20 minutes for each participant.

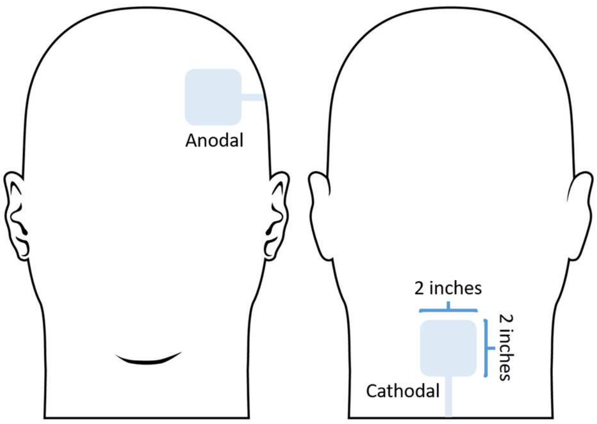

Figure 1. The electrode position for tDCS. The anodal electrode is located on the left forehead and the cathodal electrode is located on the back of the head.

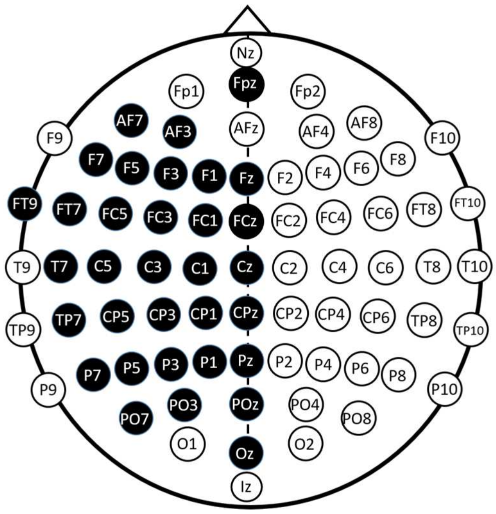

Figure 2. The electrodes positions for the 32-channel EEG acquisition. EEG signals are referenced and grounded to channel Fpz and FCz, respectively.

D. Experimental procedure

The experiment took place in a soundproofed room to minimize noises from the environment. We randomly assigned participants into two groups: receiving tDCS and receiving sham-stimulation. Each participant performs the SI experiment for six sessions, two sessions per day. The first session of the experiment in each day is labeled as pre-stimulation session. Following the first session of the experiment is the stimulation session, where participants were given tDCS or sham-stimulation. This stimulation session lasts 20 minutes and the participants were asked to rest. Among six participants, we randomly assigned three participants to the tDCS group and the other three participants to the sham-stimulation group. The second session of the experiment for each day is then performed, and the difference in the results of the first and second experiment of each day are calculated and compared between the tDCS and sham-stimulation groups to observe the effect of tDCS on the SI-based BCI system. The experiment procedure of a day is shown in figure 3 (a).

Each session of the experiment consists of 50 trials of four SI tasks for the commands: "Left", "Right", "Forward", and "Go back", and a rest condition. The experimental procedure is organized in a block-randomization manner where a block contains five trials of a task. In each block, participants were given an audio cue of the speech commands they have to imagine (or a beep sound to indicate the rest-condition task). The participants were then given a loading bar that lasts for two seconds followed by a crosshair sign on a monitor that lasts for one second repeatedly for five times. During the loading bar, participants have to imagine speaking the given commands or stay in a rest condition with their eyes opened, whereas they have to just rest during the crosshair sign.

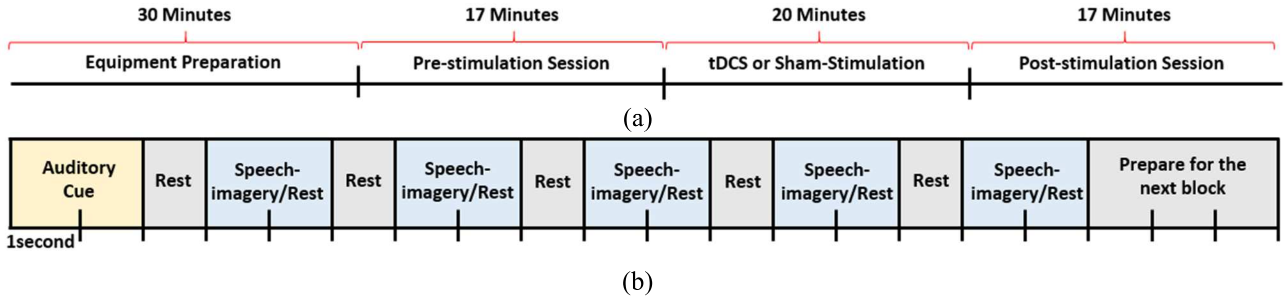

Figure 3. The experiment procedure for each day of the experiment (a) and the steps of each block of the experiment (b)

Participants were also asked to keep the body movement including eye blinking to a minimum during the SI and rest tasks. Figure 3 (b) illustrate the steps of each block of the experiment.

E. BCI performance evaluation

Raw EEG signals from all channels are first undergone data pre-processing steps before the feature extraction. First, a 60 Hz notch filter is applied to remove the power line noise. EEG signals are then segmented into 2-seconds EEG epochs and labeled to their respective class. Each EEG epoch is then decomposed into four frequency bands: Delta (0.5 Hz – 4 Hz), Theta (4 Hz – 7 Hz), Alpha (7 Hz – 14 Hz), Beta (14 Hz – 30 Hz), and Gamma (30 Hz – 100 Hz) using a 4th-order Butterworth band-pass filter.

In this study, we use Riemannian tangent space vectors projected from EEG covariance matrices as the features that represent the brain activities during the SI tasks. To extract this feature, we first calculate the covariance matrices from the EEG epochs. All EEG covariance matrices from the training session are then used to construct a Riemannian tangent space projector. For each covariance matrix C_i, its tangent space vector v_i is defined as:

$$v_i = upper(C_R^{-\frac{1}{2}} \, log_{C_R}(C_i) \, C_R^{-\frac{1}{2}}) \tag{1}$$

where $upper(\,)$ is the operator to extract the upper triangular part of a matrix and vectorize it by applying the unity weight to the diagonal elements and $\sqrt{2}$ weight to the others, C_R is the Riemannian mean of the covariance matrices and $log_{C_R}(P)$ is the logarithmic mapping of matrix P using C_R as reference. Tangent space vectors are calculated separately for each frequency band. The final feature matrix is then constructed by concatenating tangent space vectors from four frequency bands resulting in a total of 1984 features for each trial. The detailed descriptions and theory of the Riemannian tangent space projection of the EEG covariance matrix can be seen from [13].

Multi-layer extreme learning machine (MLELM) is used as the classification model. MLELM is a variation of extreme learning machine (ELM). The structure of an ELM model is similar to a normal neural network which consists of an input layer, a hidden layer, and an output layer. ELM and its variations are extremely fast when compared to other types of neural-network because they initially assign the input weight and bias randomly and these parameters are not updated throughout the learning process. For N distinct samples (x_i, y_i) where $i = 1, \dots, N$, the hidden layer is defined as:

$$h(x_i) = g(ax_i + b) \tag{2}$$

where $g(x)$ is the activation function, a is the input weights and b is the bias. Then the output layer is:

$$h(x_i)V = y_i \tag{3}$$

where V is the matrix of output weights. Considering all N training samples, equation (3) can be rewritten as:

$$HV = Y \tag{4}$$

Finally, the only learning step of ELM is done by calculating the output weight matrix V:

$$V = H^t Y \tag{5}$$

where H^t is the Moore-Penrose generalized inverse of matrix H. MLELM is constructed by using multiple auto-encoder ELMs (ELM-AE), which are a variation of ELM where the input layer is the same as the output layer) to project the features into higher features level. In other words, the $l+1^{th}$ hidden layer is constructed by an ELM-AE that takes the l^{th} hidden layer (h_l) as input. The output weights V_l learned from the ELM-AE is then used to transfer the l^{th} hidden layer to the higher level of feature space. Lastly, V_n, where n is the number of hidden layers, that connect the last hidden layer and the output layer is then learned in the same way as the original ELM. A detailed description of the ELM and its variation can be seen in [14].

F. System evaluation

We evaluate the performance of SI-based BCI in an offline manner by applying a 10-fold cross-validation method to the whole data from a session and let the samples from the same block always stay in the same fold. MLELM was constructed with the number of hidden layers equal to three and the grid search method is used to find the optimized number of hidden nodes ($\#hidden\ node = 10, 20, \dots, 200$) in each layer of the MLELM model for a session of the experiment. We also fix the random seed so that all iterations of the cross-validation produce the same initialized random parameters for all layers of the MLELM model. Finally, the mean accuracy calculated from the accuracy of all iterations of the cross-validation is used to represent the performance of the SI-based BCI system

Table 1. The SI-based BCI performance (accuracy) of all subject from pre-stimulation and post-stimulation of both sham-stimulation and tDCS method

Sham-Stimulation		**Pre-stimulation**	**Post-stimulation**	**Difference**	**tDCS**		**Pre-stimulation**	**Post-stimulation**	**Difference**
P1	Day-1	0.356	0.404	0.048	**P4**	Day-1	0.412	0.472	0.060
	Day-2	0.336	0.396	0.060		Day-2	0.424	0.444	0.020
	Day-3	0.364	0.328	-0.036		Day-3	0.480	0.460	-0.020
	Average	0.352	0.376	0.024		Average	0.439	0.459	0.020
P2	Day-1	0.400	0.368	-0.032	**P5**	Day-1	0.504	0.468	-0.036
	Day-2	0.344	0.284	-0.06		Day-2	0.44	0.548	0.108
	Day-3	0.368	0.352	-0.016		Day-3	0.496	0.568	0.072
	Average	0.371	0.335	-0.036		Average	0.48	0.528	0.048
P3	Day-1	0.344	0.344	0.000	**P6**	Day-1	0.536	0.56	0.024
	Day-2	0.420	0.332	-0.088		Day-2	0.48	0.528	0.048
	Day-3	0.336	0.388	0.052		Day-3	0.54	0.528	-0.012
	Average	0.367	0.355	-0.012		Average	0.519	0.539	0.020
Grand Average		**0.363**	**0.355**	**-0.008**	**Grand Average**		**0.479**	**0.508**	**0.029**

III. Result and Discussion

Table 1 shows the numerical results (classification accuracy) of both pre-stimulation and post-stimulation sessions of each day for all participants from both sham-stimulation group (participant P1, P2, and P3) and tDCS group (participant P4, P5, and P5). The grand average accuracy of the sham-stimulation group was 36.3% and 35.5% for the pre-stimulation and post-stimulation sessions, respectively. We can see from the result that the performance of the SI-based BCI between pre and post-stimulation sessions for the sham-stimulation group is not so different from each other (the post-stimulation group had 0.8% lower in accuracy). This suggests that the sham-stimulation does not have any effect on the participants, or at least it does not affect the brain areas that are responsible for the SI-tasks. The grand average accuracy of the tDCS group was 47.9% and 50.8% for the pre-stimulation and post-stimulation sessions, respectively. In contrast to the sham-stimulation group, the grand average classification accuracy of the post-stimulation sessions of the tDCS group was 2.9% higher than the pre-stimulation group. This indicates that the current setting of tDCS in this study can slightly boost the brain's function for the SI tasks, hence enhance the performance of the SI-based BCI system.

To investigate the effect of tDCS on the performance of SI-based BCI in long term, we also compare the average

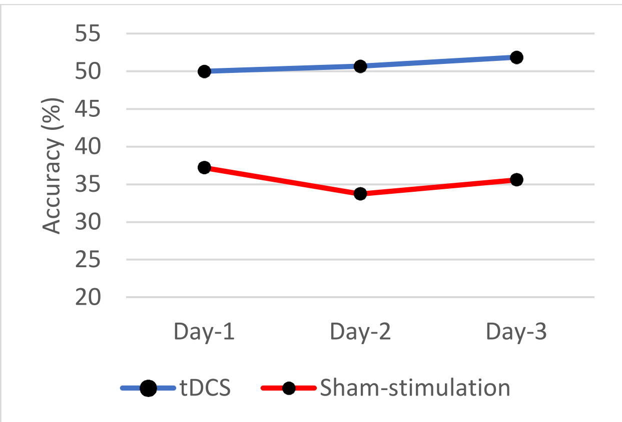

Figure 3. The averaged accuracy of SI-based BCI system in each day of the experiment. The blue line represents the tDCS group and the red line represent the sham-stimulation group.

results of the post-stimulation sessions among three days of the experiment (figure 4). From tDCS results, we can see a trend that the performance of the SI-based BCI was getting slightly better day by day. In contrast, we observe a random trend in the results of each day in the sham-stimulation group. This result suggests that tDCS might also affect the performance of SI-based BCI in a long term.

All in all, the results of this study show that tDCS can possibly enhance the performance of SI-based BCI. However, the number of participants in the current study is too small to conduct a statistical test to confirm whether the increase in the performance from the stimulation session is statistically significant or not. The future work of this study is to repeat the experiment with a greater number of participants. In addition, unlike previous studies on the effect of tDCS on MI-based BCI where tDCS is applied directly on the sensorimotor cortex area, we applied tDCS only on the left prefrontal cortex area. Therefore, it would be interesting to see the effect of tDCS on other areas in the left hemisphere such as Broca's area and Wernicke's area which are responsible for speech production and comprehension and are thought to be dominant during the SI tasks. However, these areas are covered by the EEG cap during the experiment. This means that we have to take the EEG cap off after the pre-stimulation session before applying tDCS on those areas and prepare the equipment again for the post-stimulation session. Hence, a better experimental design is needed so that the experiment would not be too burdensome for the participants.

IV. Conclusion

In this study, we conduct experiments to examine the effect of tDCS on the performance of SI-based BCI system. We applied tDCS using an anodal electrode on the left forehead and a cathodal electrode on the back of the participants' neck to stimulate the left hemisphere which is associated with speech-related functions. The results from this preliminary study show some pieces of evidence that tDCS can slightly boost the performance of SI-based BCI system. However, a greater number of participants are needed to statistically confirm this theory.

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