

Asynchronous Motor Imagery Brain-Computer Interface for Simulated Drone Control

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Abstract—Brain-computer interfaces allow direct control over devices without any physical action by the user. Motor imagery-based brain-computer interfaces analyze spatial patterns from brain signals elicited when the user imagines execution of a specific behavior. One of the ways to obtain such brain signals is with electroencephalography, which measures signals over the scalp. In this paper, we analyzed the brain patterns from when the users performed different motor imagery tasks and applied them to navigate a simulated drone. The drone was controlled asynchronously, with the user's intentions continuously analyzed throughout the entire drone control period. By navigating the drone in two different scenarios using either 4 or 6 control commands and by comparing control performance when controlling the drone with either a BCI or a keyboard, we have shown the feasibility of motor imagery for asynchronous control of drones for both two- and three-dimensional device control.

Index Terms—brain-computer interfaces, event-related desynchronization, motor imagery, drone control, asynchronous control

I. INTRODUCTION

Brain-computer interfaces (BCIs) rely on brain activity patterns to communicate with other devices [1]–[4]. One of the widely used methods to measure such brain activities is through electroencephalography (EEG), which is non-invasive and therefore does not require surgery on the user's scalp. The strength of BCIs lies in the fact that they do not require any motor execution, and EEG is therefore applicable even for patients with motor disabilities to measure their brain signals in real time [5], [6].

As discriminating brain activity patterns plays an important role for BCIs, various methods to support users to elicit different brain patterns have been researched. Some of the methods utilize visual stimuli to excite the occipital or parietal lobe. For example, steady-state visual evoked potentials utilize flickering lights of different frequencies to elicit neural activation from the occipital lobe with corresponding frequencies [7]. Another method utilizes fluctuations in brain signals, known as P300, within the parietal lobe by randomly presenting lights for choices that the user may select [8], [9]. However, such methods require gazing at their respective stimuli, which limits the user's viewpoint.

In contrast, motor imagery, a mental process in which the user imagines the execution of a specific body movement,

does not require any stimuli from the external environment. Although motor imagery is regarded as an intuitive method to map user intention directly to device commands, it also has disadvantages such as lower discrimination accuracy than stimuli-based methods, as well as limitations on the number of commands the user can use due to the limited number of motor imagery tasks the user can perform [10].

A human brain exhibits changes in neural activity in the sensorimotor cortex while motor imagery is performed. These changes include two distinguishing patterns: event-related desynchronization (ERD), a decrease of neural activity oscillation during motor imagery, and event-related synchronization (ERS), a recovery of neural activity shortly after completion of motor imagery [11]. These patterns occur in different brain regions corresponding to the different motor imagery tasks that are performed [12]. Many BCI applications utilize such patterns to control various devices such as robotic arms, wheelchairs, and other various navigating simulations [13]–[15].

In this paper, different motor imagery tasks were mapped to different movements of a simulated drone so that it could be directly controlled with the brain. Our method utilizes asynchronous control by continuously mapping discriminated brain signal patterns into user commands throughout the entire experiment. Two different scenarios were separately conducted to investigate the feasibility of our asynchronous motor imagery control method for either four or six different commands, respectively. We evaluated and compared the performances of our participants by measuring the time taken to finish the track when they either used our motor imagery BCI or a keyboard to control the drone. Furthermore, we investigated the different brain patterns elicited by the different motor imagery tasks and evaluated the classification accuracy for each participant.

II. EXPERIMENT

A. Participants

Two healthy male participants volunteered to participate in the experiments. Both participants had prior experience with motor imagery-related brain-computer interfaces. Before the experiments, participants were discouraged from consuming any food or drinks that may affect brain activity, such as beverages with caffeine.

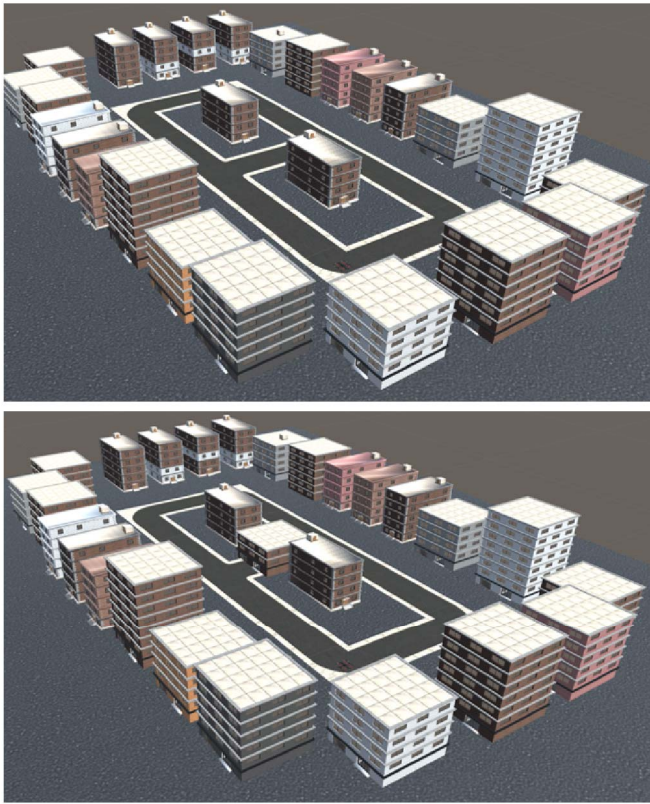


Fig. 1. A simulated track used to evaluate two-dimensional control (upper) and three-dimensional control (lower) of a drone.

B. Experimental Setup

The two experiments used two different scenarios developed with the Unity game engine (Unity Technologies, San Francisco, CA, USA), with the two scenarios being identical except for the number of motor imagery tasks used to control the simulated drone and the control tasks given to the participants, with one scenario being two-dimensional control (2D) and the other being three-dimensional control (3D).

Each scenario consisted of two different sessions: a motor imagery training session and a control session. In the motor imagery training session, participants were expected to perform motor imagery tasks as instructed by the user interface, and their EEG data was recorded to later train a classification model for distinguishing the motor imagery tasks during the control session. In the control session, participants were instructed to perform continuous motor imagery to control a drone on a figure-8 track, as shown in Figure 1.

The experiments were all held in a soundproof, dark room in order to prevent possible distractions from the outer environment. Participants sat on a comfortable chair in front of a table with a monitor screen while wearing a wet EEG cap. Participants were instructed to place their hands on the desk and to finish both the motor imagery training and control sessions while minimizing movements such as muscle movement and eye blinks. Prior to motor imagery training, participants were asked to choose and report which motor imagery task they

would use for each movement when controlling the simulated drone.

C. Motor Imagery Training

A motor imagery training session consisted of a minimum of 6 trials to a maximum of 12 trials of sequential motor imagery tasks, depending on the requests from the participants. A single trial consisted of 4 different motor imagery tasks for the 2D control scenario and 6 different motor imagery tasks for the 3D control scenario. Each motor imagery task was 12 seconds long.

Within a single motor imagery trial for the 2D control scenario, a right arrow, a left arrow, an upward arrow, and a cross sign appeared sequentially on the screen, with each sign corresponding to one of the four motor imagery tasks. The right and left arrows indicated right and left rotations of a drone, respectively, the upward arrow indicated forward movement of the drone, and the cross sign indicated stopping the drone. Participants were instructed to rest when shown the cross sign. All the signs that appeared during the 2D control scenario were colored in green. A single motor imagery trial for the 2D scenario thus lasted for approximately 48 seconds.

Within a motor imagery trial for the 3D control scenario, two additional signs, an upward arrow in red indicating an upward movement of the drone, and a downward arrow in red indicating a downward movement of the drone, were added. A single motor imagery trial for the 3D control scenario therefore lasted for approximately 72 seconds.

D. Control Experiment Design

In the control session, participants were first instructed to control a simulated drone with our BCI and finish a given course. In the 2D control scenario, participants were able to control the drone by performing forward movement, left rotation, right rotation, or stopping using the same motor imagery tasks performed during motor imagery training. The simulated course consisted of a figure-8 track with buildings serving as obstacles to be avoided, and participants were instructed to move through the track and return back to the initial location without any collisions.

In the 3D control scenario, participants were able to additionally perform upward and downward movement to control the drone. The simulated course for the 3D control scenario was similar to that of the 2D control scenario, with an additional building located in the middle of the figure-8 track. When the participants reached this building, they were instructed to perform upward and downward movements to pass over the building without collision.

After finishing the control sessions for both scenarios with the BCI, the participants went through each scenario once more but with a keyboard instead of the BCI to control the simulated drone. When controlling the drone with a keyboard, pressing a key caused an immediate response by the drone by performing the corresponding movement.

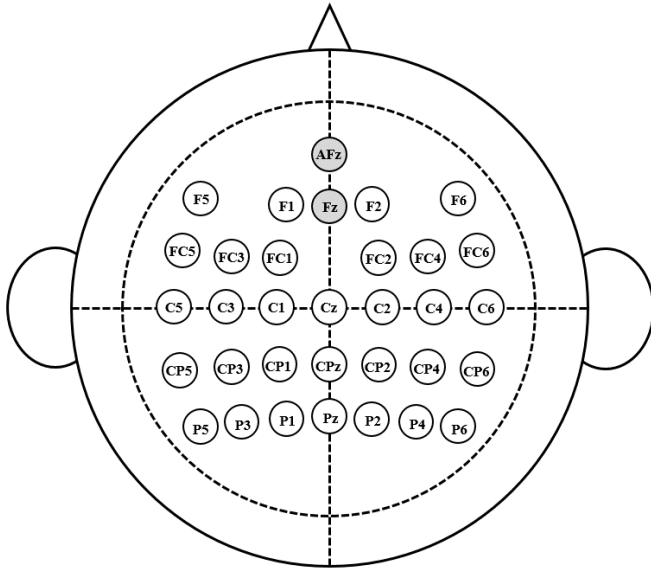


Fig. 2. The electrode positions used in the two experiments.

III. METHODS

A. Signal Acquisition

To acquire brain signals from the scalp of the participants, BrainProducts' actiCAP and actiChamp (BrainProducts, Munich, Germany) were used. As shown in Figure 2, a total of 33 electrodes, with most of them near the sensorimotor cortex, were placed to record EEG data when participants were expected to perform motor imagery, with AFz and Fz as the ground and reference electrodes, respectively. The EEG data was sampled with a 500 Hz frequency rate, and the electrodes were located with accordance to the international 10-20 system. To obtain brain signals of high quality, the impedance of each electrode as seen in BrainVision was kept lower than 10 k Ω .

B. Classification Model for Motor Imagery

Considering that the number of motor imagery tasks used differs for the two scenarios, the machine learning methods used also slightly differ.

The EEG data acquired in the training session was pre-processed using data augmentation by splitting the signals for 2D control into 2-second time windows with a stride of 1 second and those for 3D control into 3-second time windows with a stride of 1 second in order to increase the amount of data for training the model. As for the control sessions, the most recent 2-second window and 3-second window of EEG data for 2D and 3D control, respectively, were used to perform motor imagery classification in real time. Classification was performed once every second in order to asynchronously control the simulated drone, and the drone moved only when the two most recent classification results indicated the same command.

In the 2D scenario, the EEG data was band-pass filtered between 8 and 28 Hz to extract signals related to motor

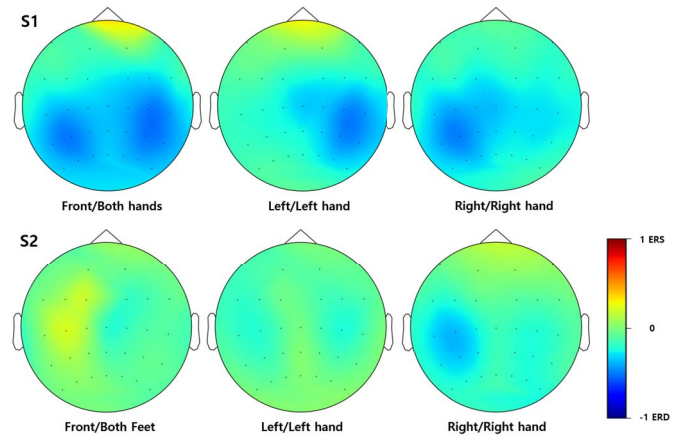


Fig. 3. The ERD ratio topomap of participants for different motor imagery tasks with respect to the resting state from the training data of the two-dimensional scenario.

imagery. To strengthen spatial patterns within the acquired EEG data, common spatial pattern (CSP) was used on the extracted signals [16]. Fisher's linear discriminant analysis (LDA) was performed on the transformed data to perform dimensionality reduction and classify motor imagery tasks with the EEG signals [17].

In the 3D scenario, acquired EEG data was band-pass filtered between 8 and 36 Hz, and the filter-bank common spatial pattern (FBCSP) was used to extract spatial features of the data. Each filter was 4 Hz wide, resulting in a total of 7 filter banks [18]. The extracted data was then classified using LDA.

C. Evaluation

To evaluate the model and to validate the motor imagery performance of participants, cross-validation was performed with the EEG data from the training session. Cross-validation was performed in a k-fold manner where k represents the number of training trials each participant performed. A single trial was used as testing data while the remaining sessions were used as training data for the model, and the accuracies from each fold were averaged to evaluate the motor imagery performance from the training session.

The trajectories of the drone during the testing sessions were also reproduced by recording the position of the drone once a second throughout each control session. The trajectories of the drone were then plotted to compare results.

IV. RESULTS

A. Brain Activity Patterns from Different Motor Imagery Tasks

The brain activity patterns from the two participants during the 2D control scenario and the 3D control scenario are shown in Figures 3 and 4, respectively. For 2D control, both participants chose to perform left hand, right hand, and resting motor imagery to execute the left rotation, right rotation, and stopping command, respectively. As shown in Figure 3, participant S1 chose to perform both hands motor imagery,

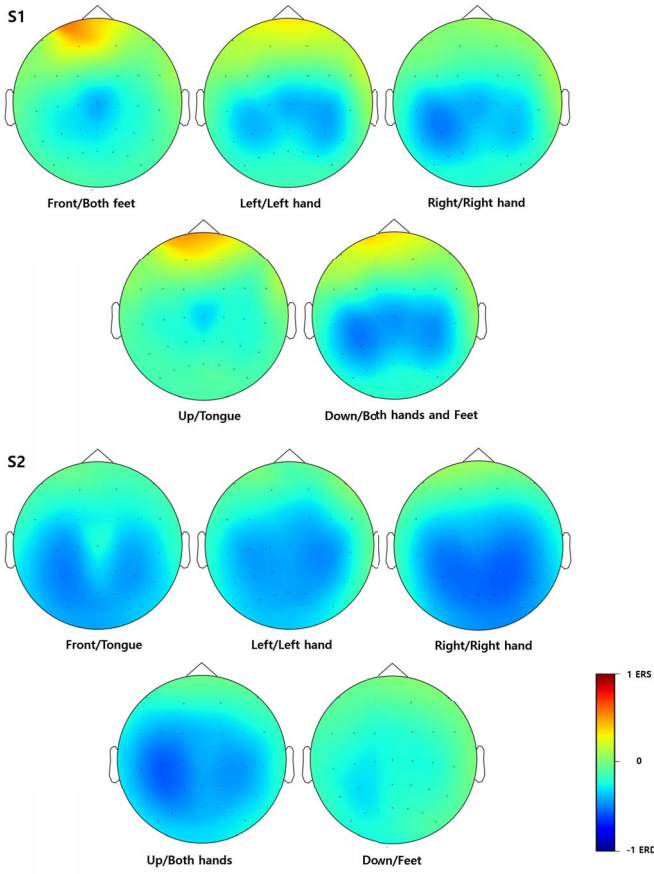


Fig. 4. The ERD ratio topomap of participants for different motor imagery tasks with respect to the resting state from the training data of the three-dimensional scenario.

while participant S2 chose to perform both feet motor imagery instead for forward movement. For 3D control, the participants used a combination of hands, feet and tongue motor imagery to control the drone as shown in Figure 4.

B. Experimental Results for Two-Dimensional Control

The cross-validation results for the participants using motor imagery and the elapsed time to finish using BCI and keyboard for the 2D control experiments are shown in Tables I and II. As shown in the table, participants 1 and 2 had a cross-validated accuracy of 91.3% and 70.8%, respectively, for classifying between four different drone control movements. The two participants took 390 and 458 seconds using BCI and 297 and 308 seconds using the keyboard, respectively. No collisions occurred during the two-dimensional scenarios, as seen in the trajectories in Figure 5.

C. Experimental Results for Three-Dimensional Control

The cross-validation results of 6-class BCI, as well as elapsed time for the 3D control scenario using the two different interfaces are also shown in Tables I and II. As shown in the table, the cross-validation results were 87.3% and 80.9% for participants 1 and 2, respectively, with an elapsed time of 702 and 728 seconds using BCI and 402 and 420 seconds using the

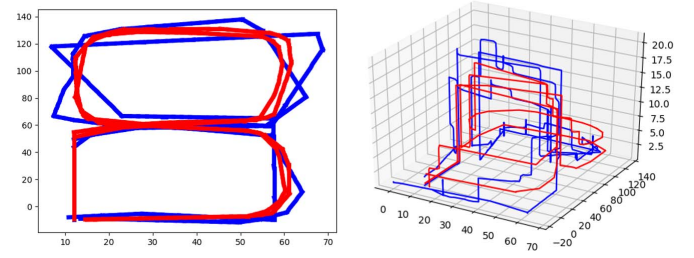


Fig. 5. The trajectories of the simulated drone when controlled with a keyboard (red) or BCI (blue) during the two-dimensional scenario (left) and the three-dimensional scenario (right).

keyboard. No collisions occurred during the three-dimensional scenario as well, as seen in Figure 5.

V. DISCUSSION

In this study, we applied machine learning methods to control a simulated drone using both 4-class and 6-class motor imagery. Participants were able to finish the scenarios without collision via an asynchronous method in which the mental states of the participants were continuously considered to control the drone until the drone returned to its initial position. By plotting the topomap of the participants when they were performing different motor imagery tasks, we can see different brain activity patterns, specifically from the sensorimotor cortex, corresponding to each task. Furthermore, we additionally compared the results for driving the drone with a BCI and with a keyboard.

Although controlling the drone using the BCI was not faster than when using the keyboard, both participants were able to finish the 2D control scenario with our BCI within 1.5 times the time they took when using the keyboard. Participants were also able to finish the 3D scenario within 2 times the time they took with the keyboard. Although the BCI results did not exceed the results with the keyboard, we have seen the potential of using a BCI to control devices using different

TABLE I
CROSS-VALIDATION ACCURACY RESULTS

Subjects	4-class MI (2D)	6-class MI (3D)
S1	91.3	87.3
S2	70.8	80.9
AVG	81.1	84.1

TABLE II
ELAPSED TIME FOR THE CONTROL SCENARIOS

Subjects	BCI (2D)	KBD (2D)	BCI (3D)	KBD (3D)
S1	390	297	702	402
S2	458	308	728	420
AVG	424	302.5	715	411

forms of brain patterns elicited by different motor imagery tasks.

Although both of our participants were able to complete both scenarios without collision, this may only have been possible due to the fact that both participants had prior experience using multi-class motor imagery BCIs and therefore had high classification performance. Other users with little experience with or low performance when using multi-class motor imagery BCIs should consider using other training methods such as neurofeedback training methods or other visual feedback to support imagination so that they can improve their motor imagery performance prior to using our interface [19], [20].

As the strength of brain signals from each individual varies between different motor imagery tasks, it may be important to analyze which motor imagery task is the most suitable for each participant during motor imagery-based BCI control. As seen from the topomaps of the participants in which the brain patterns from each individual differ even though they performed the same motor imagery task, more studies regarding which motor imagery tasks would better induce distinguishing brain patterns for different individuals may need to be conducted to better control devices. Furthermore, applying other methods to further improve motor imagery performance, such as utilizing adaptive BCIs, would be suitable as other mental components may distract brain patterns during online control [21]–[23].

VI. CONCLUSION

In this study, we applied machine learning methods to control a simulated drone asynchronously. Both participants were able to successfully finish the given track using both 4-class and 6-class motor imagery discrimination. Future work on improving motor imagery-based BCIs for asynchronously controlling devices may close the gap between BCI performance and performance with existing, widely used interfaces.

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