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Assistive Technology Design and Preliminary Testing of a Robot Platform Based on Movement Intention using Low-Cost Brain Computer Interface

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***Abstract*— The process through which children learn about the world and develop perceptual, cognitive and motor skills relies heavily on object exploration in their physical world. New types of assistive technology that enable children with impairments to interact with their environment have emerged in recent years, and they could be beneficial for children's cognitive and perceptual skills development. Many studies have reported on brain computer interface (BCI) research. However, a conventional electroencephalography (EEG) system is generally bulky and expensive. It also requires special equipment and technical expertise to operate successfully. In this study, a compact low-cost EEG system was used to detect signals related to movement intention and control a mobile robot control. EEG signals of three non-disabled adults were acquired by the BCI system and the movement intention was classified during physical movement and motor imagery. The average classification accuracies achieved during testing were 56.4% for the motor imagery and 72.7% for the physical movement. The results show moderate classification accuracy for the motor imagery; however, the classification accuracy for the physical movement was high for all the subjects. Even though further improvement of the system is still needed, the experimental results demonstrated the feasibility of a BCI-based robotic system that is affordable and accessible for many people including children with disabilities.**

Keywords—Assistive Technology; Brain Computer Interfaces (BCI); Event Related Desynchronization (ERD); Robot Control

I. Introduction

Cognitive development refers to the development of children in terms of thinking, resolving, learning, feeling, and knowing the environment [1]. The developmental process of cognitive and perceptual skills for children depends heavily on object exploration in their physical world [2, 3]. Motor and perceptual experiences in our daily activities can also assist in cognitive development. Physical manipulation of objects has been identified as a critical motor experience that enables children to learn skills, such as the emergence of symbols, referential communication and the understanding of relations between objects [4].

Play is a natural way in which all children interact with their social and physical environments in order to explore and discover different objects and experiences [5]. For children who have severe physical impairments, one of the biggest concerns is a lack of opportunities for meaningful play activities with objects. Robots such as the Play-ROB [6] and Lego robots [3] enable children with cognitive and physical disabilities to manipulate objects in play. Interfaces for these robots were, respectively, a joystick [6] or switches [3]. Studies have successfully demonstrated the feasibility of using these interfaces in robot and assistive technology control [3, 6, 7]. Simple button switches are some of the commonly used human interfaces in the field of assistive technology [8]. The switches can be placed at different anatomical locations and replaced with different types of switch devices; however joysticks provide users with more direct control than switch interfaces. Joysticks require some degree of physical ability to operate and may be difficult for children who have little voluntary and repeatable muscle control. The objective of this study is to determine whether the use of biological signals to detect movement intention as an input for robot control may improve robotic manipulation of objects.

Electroencephalography (EEG) is a biological signal that indicates the brain's activity and can be detected by electrodes placed on the surface of the scalp [9]. EEG signals are generally categorized based on the type of response [10]. One response is event-related desynchronization (ERD). ERD can be observed over the motor cortex during movement ("physical movement") or imagination of movement ("motor imagery"). For people with severe physical disability such as those who have limited voluntary movement, the ERD response can still be observed [11-13]. Huang, et al. [14] tested BCIs for 2-dimensional cursor control based on ERD during motor execution and motor imagery with 5 non-disabled participants. Classification methods using Linear

Discriminant Analysis (LDA), Decision Tree, and Support Vector Machine (SVM) provided as high as 88% accuracy rate for the physical movements and 73% accuracy rate for the motor imagery. In addition, previous BCI studies indicated that control of ERD can be enhanced by BCI training with biofeedback such as visual, auditory, or vibrotactile feedback [15-17]. In the study of Pichiorri, et al. [15], ten non-disabled participants underwent 4 weeks of BCI training with visual feedback. No significant difference was found between before and after BCI training, but 75%-96% accuracy was consistantly achieved. These studies indicate that ERD is potentially a feasible channel for brain-computer interface (BCI) for children with neurological impairments. However, a conventional EEG system is generally bulky and expensive. It also requires specialized equipment and technical expertise to operate successfully. Therefore, conventional EEG systems are not suitable for many situations such as play activities at home or clinical practice outside of the research laboratory.

Today, several low-cost BCIs, such as Emotiv EPOC (EMOTIV Inc. San Francisco, CA, USA) and NeuroSky (NeuroSky Inc, San Jose, CA, USA), are commercially available. They are compact and more accessible to the general public compared with conventional EEG systems. In a study by Frey, et al. [18], a new low-cost EEG system was developed. This EEG system was designed for novice users to observe their own EEG signals in real-time. The system allows people to visualize, understand and interact with their own brain activity, and the authors promote it as a relevant training and mediation tool. A study by Vamvakousis and Ramirez [19] detected ERD response caused by imagery and real lower limb movements using the Emotiv EPOC with healthy subjects. Since standard location of Emotiv electrodes do not cover the motor cortex area, the Emotiv EPOC needed to be customized.

It could be beneficial to investigate the feasibility of a robotic system for children with severe physical disability by using a compact low-cost BCI. As a first step, we trialed the system with adults. EEG data during movement or imagination of movement and ERD responses were analyzed and used to classify the intentions of movements for mobile robot control with non-disabled adults.

II. Methods

A. Participants

Three right-handed adults without disability, a 42-year-old male (Subject 1), a 23-year-old male (Subject 2), and a 23-year-old female (Subject 3), participated in the study. Subject 1 had BCI experience in a previous study, while Subject 2 and Subject 3 had no prior BCI experience.

B. Materials

The robotic system included a Windows PC, an OpenBCI (OpenBCI, Inc., Brooklyn, NY, USA), and a Lego Mindstorms NXT (Lego Group, Billund, Denmark). The OpenBCI (Figure 1) is a low-cost BCI which is portable, programmable, open-source EEG platform that gives access to brain signals. The OpenBCI measured the user's brain signals over the cerebral cortex with a set of gold cup electrodes. The Lego Mindstorms was used as a mobile robot to be controlled by EEG data. Both the OpenBCI and Lego Mindstorms were connected with the PC wirelessly via Bluetooth. A schematic diagram of this set up is shown in Figure 2.

MATLAB (MathWorks, Inc., Nadick, MA, USA) was used for the EEG data acquisition and signal processing. In addition, MATLAB Statistics and Machine Learning Toolbox was used for designing and validation of the classifiers based on the ERD response. LabVIEW (National Instruments, Corp, Austin, TX, USA) was used to control the Lego Mindstorms based on the EEG signals.

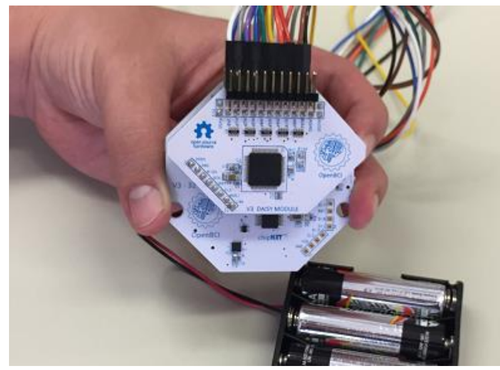

Fig. 1. OpenBCI Brain Computer Interface

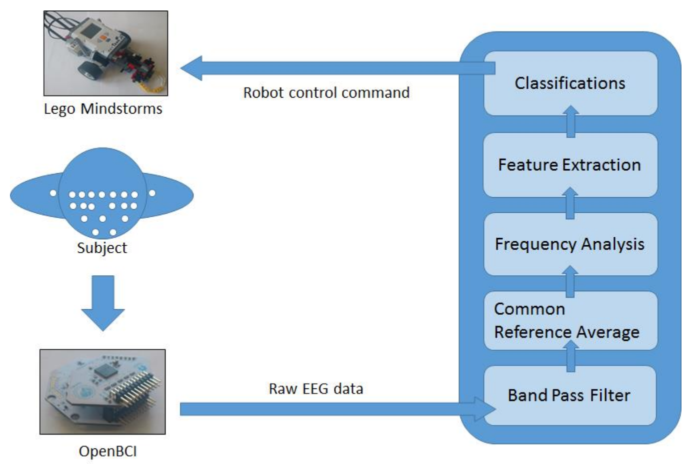

Fig. 2. Schematic Diagram of the Experimental Setup. EEG signals are acquired from subjects by OpenBCI. The signals are digitally filtered and used to design classifiers based on the ERD during physical movements and motor imageries. A Lego Mindstorms robot is controlled offline by the EEG signals with the classifiers.

C. Experiment

The experiments were conducted in two sessions on different days. There were two types of tasks in each session: EEG measurements during physical movement and EEG measurements during motor imagery. Participants sat in a comfortable position and looked at the computer screen in front of them. For the physical movement task, according to a visual cue displayed on the computer screen, they were asked either to stay at rest or perform internal and external rotation of the shoulder with their dominant arm while the elbow was in 90 degrees of flexion (Figure 3). For the motor imagery task, according to a visual cue displayed on the computer screen, the participants were asked to imagine either rest (i.e., no movement) or movement of their limbs without moving their arms. In each task, the participants were asked to perform three trials.

In each trial, a blank screen was displayed on the computer screen for the first four seconds. For the next six seconds, the visual cue indicating 'MOVE' was displayed. The participants performed either physical movement or motor imagery until the display was blank again, which lasted four seconds. When the visual cue indicated 'REST', the participants relaxed for the next six seconds. Figure 4 shows the timing diagram of the motor imagery and physical movement tasks. These visual cue sequences were repeated ten times in each trial. In total, six trials for physical movement and six trials for motor imagery were collected over the two sessions per participant. No BCI training was provided to the participants before the experiments.

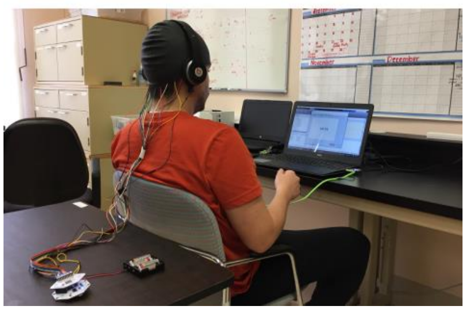

Fig. 3. Trials of the Physical Movement Task with a Subject

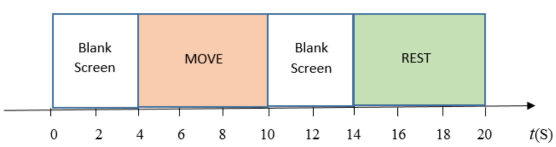

Fig. 4. Timing Diagram of the Task for the Physical Movement and Motor Imagery

D. EEG Data Collection

Sixteen channels of EEG data were recorded during the trials with the OpenBCI. All the electrodes were located on the surface of the scalp over the area of the central sulcus, parietal lobes, and occipital lobes of the brain. The locations of the electrodes were C1, C2, C3, C4, CZ, CP1, CP2, CP3, CP4, CP5, CP6, P3, P4, PZ, O1, and O2 according to the 10-20 international system, and the reference and ground were placed at A1 and A2 respectively. The EEG data were sampled at 125Hz and pre-processed with 3Hz - 40Hz FIR band pass filter and Common Average Reference (CAR) to remove the noise and offset.

E. Analysis

From the trials, six EEG datasets for the physical movement tasks and six EEG datasets for the motor imagery tasks were obtained per participant. In each task, three datasets were randomly chosen as the training datasets for designing classifiers, and two datasets were randomly selected for an evaluation of the robot control. The last dataset was used to fall back upon in case of failure to save EEG data. The following were the procedures of the classifier design and the system evaluation.

1) Feature extraction: Power Spectrum Density (PSD) using a hamming window was computed in different lengths of the EEG signals (e.g., every 63, 125, 188, and 250 samples). Since the EEG was sampled at 125Hz sampling rate, the length of the EEG indicated the time frame of the PSD computation. In other words, to compute the PSD every 63, 125, 188, and 250 samples means that the PSD was computed every 0.5, 1, 1.5, and 2 seconds respectively. The shorter time frame enabled the robot to be controlled closer to real-time. The frequency range where the ERD occurred was determined according to the EEG data for individuals by visual inspection. The frequency range was divided into four frequency bands and the absolute power in each frequency band was computed. The absolute power in each frequency band was extracted as the features for the classification design. These features were extracted from all 16 EEG channels. Therefore, 64 features were obtained from the EEG data in each time frame.

2) Classification: Three types of machine learning classification methods were used to compare classification accuracy between periods of movement and rest. The classification methods used were Linear Discriminant Analysis (LDA) [20], Linear Support Vector Machine (SVM) [21], and Neural Network (NN) [22]. The LDA is one of the simplest linear discriminant algorithms. It finds a hyperplane to separate the classes based on the means of the samples in each class. Like the LDA, the SVM is also a classification method using a hyperplane to separate the classes. However, the SVM finds a separation hyperplane that has the largest distance of the nearest samples of any class [21]. The NN is a nonlinear classification method, and the network generally consists of an input, hidden layer, and output layer. Neurons in the hidden layer work as a function that takes some weighted inputs from the input layer and then returns an output to the output layer. The weights were determined by adjusting to minimize error according to the training samples. In this study, a NN with 30 neurons in a single hidden layer was used. Since the EEG patterns were different depending on the participants, the classifiers were designed for each individual based on the EEG datasets from the trials.

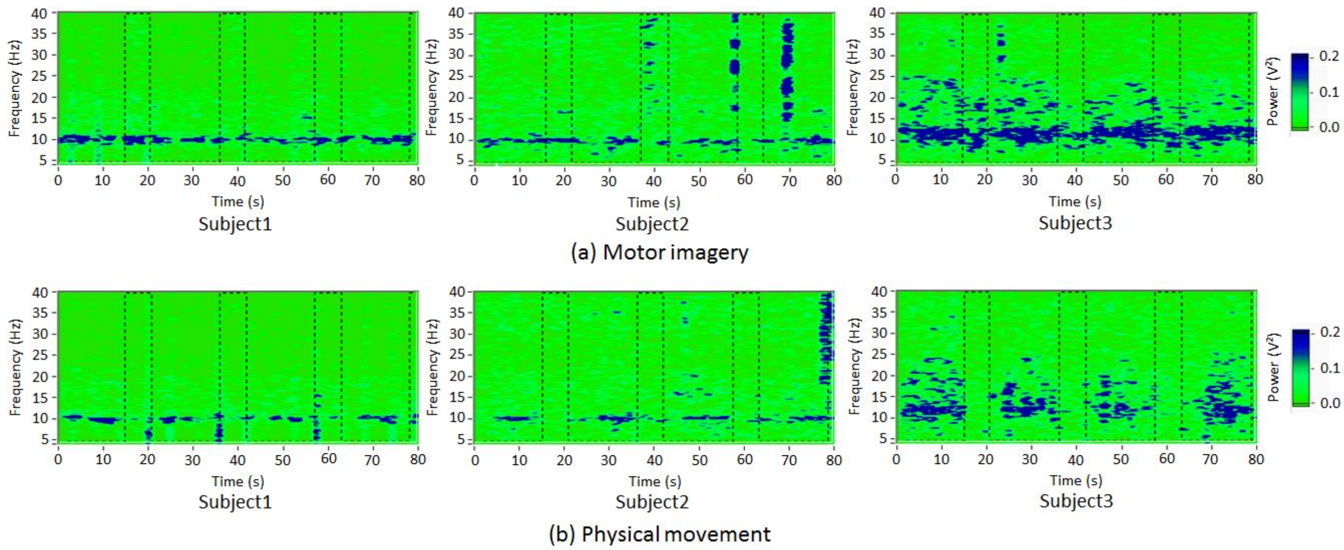

Fig. 5. Time-Frequency Analysis of the EEG signals of Subject 1 (Left), Subject 2 (Center), and Subject 3 (Right) during the Motor Imagery Task (Top) and the Physical Movement Task (Bottom)

3) Evaluation: 10-fold cross validation was used to check the classification accuracy during classifier design with the training set, which was three datasets combined. Using each classifier, the two test datasets were used to check the classification accuracy while controlling the robot. The EEG test datasets were played back by software at 125 Hz, which is the same frequency as the sampling rate of the OpenBCI, and based on the classification sent a control command to the Lego Mindstorms for either MOVE or STOP.

The classification accuracy in all the following conditions was measured: Tasks (i.e., Physical Movement and Motor Imagery), Classification methods (i.e., LDA, NN, and SVM), and Time frame of PSD (i.e., 0.5 sec, 1 sec, 1.5 sec, and 2 sec).

III. RESULTS

A. EEG data analysis

EEG data were analyzed in both the frequency and time domains to investigate the intention of movement for each subject. Figure 5 shows the time-frequency analysis of the EEG at the C3 location during the physical movement and motor imagery tasks. In the graphs, the narrow sections separated by the dotted lines indicate the periods of MOVE of the visual cue, and the broad sections indicate the periods of blank screen and REST of the visual cue. The larger values of power are displayed in blue; the green colored regions represent values that are near zero in magnitude. The graphs for physical movement show a decrease of the power in frequency for each subject during the movement for all the subjects, while the graphs for motor imagery do not show the decrease as clearly. Figure 5 reveals an individual frequency range of the ERD responses. In this study, the alpha frequency band (8 – 14 Hz) was used for each subject to compute PSD to extract the features in the next steps.

B. Test performance using different classification methods

One-way ANOVA with the classification type as a factor revealed significant differences between all the classification methods except for the physical movement task by Subject 3 ($p < 0.05$) as shown in Table 1. Table 1 also shows the mean accuracy of LDA and SVM was higher than the NN for both the motor imagery and physical movement tasks.

Figure 6 shows the average accuracy of the classification methods based on the different time frames of PSD. These results indicate that the classification accuracies of LDA and SVM improve as the time frame increases. However, the results of NN over the different time frames differed from the results of the LDA and SVM. The correlation between accuracy and time frame was weaker for NN (R^2 =0.12 for motor imagery and R^2 =0.53 for physical movement) than LDA (R^2 =0.35 for motor imagery and R^2 =0.87 for physical movement) and SVM (R^2 =0.20 for motor imagery and R^2 =0.68 for physical movement).

TABLE I. CLASSIFICATION ACCURACY OF DIFFERENT CLASSIFICATION METHODS

	Classification Accuracy (%)					
	Motor Imagery			**Physical Movement**		
	LDA	**NN**	**SVM**	**LDA**	**NN**	**SVM**
Subject 1	49.98* (4.05)	53.82* (4.80)	53.55* (4.62)	74.62* (6.72)	65.74* (8.90)	76.31* (6.84)
Subject 2	62.78* (9.00)	57.56* (8.18)	63.12* (9.58)	71.17* (9.80)	64.10* (8.59)	74.10* (7.78)
Subject 3	56.40* (4.15)	53.55* (4.46)	56.83* (2.60)	74.74 (8.93)	75.78 (9.35)	77.55 (10.12)
Mean (SD)	**56.38 (8.03)**	**54.98 (6.21)**	**57.83 (7.37)**	**73.51 (8.59)**	**68.54 (10.20)**	**75.98 (8.31)**

*Significant differences $p < 0.05$ by ANOVA

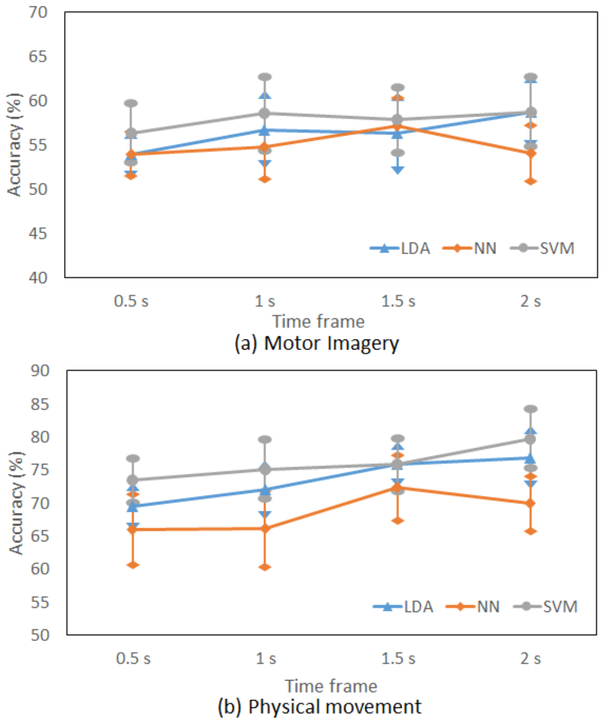

Fig. 6. Accuracy of the Classification Methods based on the Different Time Frames of PSD for the Motor Imagery Tasks (Top) and the Physical Movement Tasks (Bottom)

C. *Comparison of classification accuracy for 10-fold cross validation and testing with robot for SVM*

The SVM classifier was used here because it had the best performance above. No significant differences were found between the mean classification accuracy of SVM with 10-fold cross validation and testing with the robot for the physical movement task, and classification accuracy was higher than 70% in all the cases (Figure 7). For the motor imagery task, classification accuracy was significantly higher for validation than testing with robot for Subjects 1 and 3 ($p < 0.05$).

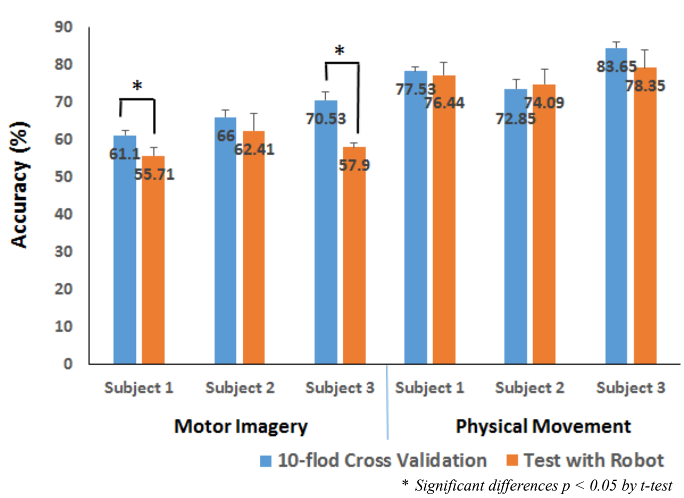

Fig. 7. Classification Accuracy of SVM for 10-fold Cross Validation and Testing with Robot.

IV. Discussion

The feasibility of a robotic system using a low-cost BCI was investigated. The intention of movement was successfully classified during movement and imagination of movement based on EEG data and used to control a mobile robot.

A longer time frame of PSD results in a higher frequency resolution and the more accurate resolution led to a higher classification accuracy for LDA and SVM in 1.5 and 2 sec time frames. However, NN achieved better accuracy with a time frame of 1.5 sec compared to the time frame of 2 sec (Figure 6). This is probably because the smaller training dataset size impacts the result of the classification accuracy of the NN. A longer time frame requires more EEG data to compute the PSD. Therefore, it reduces the number of samples of the classifier's training datasets. Even though the size of training datasets should impact all types of classification methods, in this study, LDA and SVM were more robust and accurate in all cases. For robot control, the time frame of 0.5 sec makes it possible for the mobile robot to operate closer to real-time. However, the accuracies were not reliably high with that time frame. The time frame of 1 sec and 1.5 sec for SVM worked fairly well in this experiment.

No significant differences were found between the SVM classification accuracy with 10-fold cross validation and the test result with robot for physical movement (Figure 7). A possible reason for the significant differences between these results during the motor imagery tasks for Subject 1 and Subject 3 is that it was difficult for them to produce the constant ERD during the motor imagery tasks. Their EEG datasets may not have contained clear ERD responses. Since it is known that EEG patterns are different depending on the individual, these results should not be surprising. According to feedback from Subject 1 and Subject 3, they tried to change the way they imagined movement occasionally and did not imagine the same movement throughout the trials. In contrast, Subject 2 imagined the same movement which was lifting a weight with his dominant arm in all the trials. This could be another possible reason for the lower accuracy of Subjects 1 and 3. Different brain regions are responsible for different functions and different parts of the body. Thus, imagining different parts of body movement result in different brain activity patterns. This might have affected the accuracy of the classification results and will be addressed in future protocols.

The results of this study show similar classification accuracy ranges reported in previous BCI studies [15-17]. Having biofeedback, for example, visual feedback of the ERD levels displayed on the computer screen, and training to imagine movement can help to improve the performance of the motor imagery task [15]. In this study, the participants did not receive any BCI training before the experiments. If BCI training was provided to participants before the experiments, we expect that the participants would have performed better on the motor imagery tasks. In contrast, the classification accuracies of the physical movement task were reliably high for all the subjects despite having no prior BCI training.

V. Conclusion

A low-cost BCI, OpenBCI, was used for ERD classification and successfully controlled a mobile robot using EEG data. This implies that OpenBCI can be a potential brain computer interface in the field of assistive technology.

This study showed that the ERD responses varied among different individuals. It might be difficult for some people to generate the ERD during the motor imagery tasks. However, training sessions prior to the BCI trials are expected to improve their performance. In contrast, ERD response during physical movement can be reliably measured and discriminated by linear classification methods.

In the future, we want to make the system easier to use and improve the classification accuracy for practical use. For example, minimizing the number of electrodes is one way to make the system easier to set up. Also, increasing the sampling rate would have a great impact on the classification accuracy for the system. As preliminary testing for BCI robot control, in this study, the robot was controlled with the test datasets recorded from participants. For the next step, we will develop the robotic system to acquire, process, and classify the EEG all in real-time. This can be applied to many applications of assistive technology, such as assistive robot control, wheelchair maneuvering, and prosthesis control.

The ultimate goal of this study is to develop a compact low-cost BCI-based robotic system for children with disabilities. The subjects who participated in this study were all non-disabled adults. Therefore, in future studies, the system needs to be validated with clinical populations including children with physical impairments.

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