GENERATING FORBIDDEN REGION VIRTUAL FIXTURES BY CLASSIFICATION OF MOVEMENT INTENTION BASED ON EVENT-RELATED DESYNCHRONIZATION

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ABSTRACT

The development of children's cognitive and perceptual skills depends heavily on object exploration and manipulative experiences. New types of robotic assistive technologies that enable children with disabilities to interact with their environment, which prove to be beneficial for their cognitive and perceptual skills development, have emerged in recent years. In this study, a human-robot interface that uses Event-Related Desynchronization (ERD) brain response during movement was developed. A haptic robot generates force feedback to constrain the user's hand motion into a defined region using a Forbidden Region Virtual Fixture (FRVF). Two channels of electroencephalography (EEG) brain signals were acquired and used to design classifiers to discriminate the pattern of brain signals between "movement" and "rest" during the operation of the robot. The highest ERD classification accuracy achieved was 69.4%. With the classifier, ERD-based FRVFs were tested in a simple robot operation task with two non-disabled adults. The virtual wall triggered by ERD successfully blocked the motion of the two participants on average 7 and 6.4 out of 10 times, respectively. Although further improvement of the system is still needed, the experimental results demonstrate the potential of the ERD-based FRVFs in robot control for a clinical population.

Index Terms**—** Brain–computer interface (BCI), electroencephalography (EEG), event-related synchronization (ERD), haptics, robot, virtual fixtures.

1. INTRODUCTION

The experience of object manipulation in a physical environment has a large influence on development of cognitive skills in children [1, 2]. Manipulation has been identified as a critical motor experience that enables children to acquire skills such as the emergence of symbols, referential communication, and the understanding of relations between objects [3].

For children who have severe physical disabilities such as stroke or cerebral palsy, one of the biggest concerns is lacking opportunities for meaningful manipulation tasks, often in the context of play activities [4]. This lack of opportunities may negatively affect the progressive development of their learning skills and mental growth [5]. Unlike an adult who has lost acquired functions, many children with neurological impairments are born with functional deficits. In this case, the children may not have many opportunities to find out about the world through manipulative experiences.

Play is an enjoyable and natural way in which all children interact with their social and physical environment in order to explore and discover different objects and experiences [6]. Robots can be utilized to facilitate the play activities of children with impairments. Simple button switches are common human-robot interfaces used as a means of robot control by children with physical impairments. Switch interfaces require the cognitive ability to understand how the switches relate to the robot operation, and children's understanding of robot control is correlated with the child's cognitive age. In comparison, joysticks provide users with a more intuitive robot operation; however, children who have physical impairments may not be physically able to manipulate the interface in the desired direction.

Kinesthetic or other types of guidance through the user interface can help to accomplish control of the robot in spite of the disability. In a study by Atashzar et al. [7], a haptics-capable human-robot interface was used to teleoperate another robot performing a task. The haptic capabilities of the system allowed forces occurring at the task-side robot to be felt through the user-side haptics-capable robot. A system such as this can also limit the user's hand motion into a defined region using the so-called Forbidden Region Virtual Fixtures (FRVFs), so that the interface can help the users traverse the non-forbidden regions of the environment more efficiently. In our previous research [8], a computer vision system was used for defining appropriate locations of the FRVFs, so the users could rely on the FRVFs and move their hand along the outside of the fixtures to reach the target destination. With ten non-disabled participants and one participant with physical impairments, the system successfully restricted the users' hand movement to a defined region during robot operation. This robot function could be beneficial for people with physical impairments, especially people who do not have the skills to correctly operate a robot. However, by using only computer vision-based FRVFs, the system does not know where the user intended to move the robot.

Electroencephalography (EEG) is a measure of the brain's activity as detected by electrodes placed on the surface of the scalp [9]. Today, several consumer Brain-Computer Interface (BCI) instruments are available on the market. They are compact and low-cost compared with conventional BCIs. EEG signals are generally categorized based on the type of response. A type of brain response called Event-Related Desynchronization (ERD) appears during movement or preparation for movement of parts of the body. Therefore, observing ERD makes it possible to detect the user's intended motion. Although children with physical disabilities have limitations of movement, it is still possible to generate ERD with only motor imagery. Many studies have successfully demonstrated a significant benefit of the ERD-based BCIs with both non-disabled adult participants and adult participants with physical impairments [10-13]. For example, Huang, et al. [13] 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. López-Larraz, et al. [12] tested four subjects with a hemispheric stroke and attempted to classify their EEG patterns while they moved the affected limb. The study successfully demonstrated high classification accuracies (i.e., in the range of 80% – 92%). However, to the best of our knowledge, very few studies have actually tested ERD-based BCI in robot control for children with disabilities [14]. ERD for children with neurological impairments might be a feasible access pathway to control robots and to help children with motor impairments to explore their environment using assistive robots. As a first step, we trialed the system with adults.

In this study, movement-related brain activity manifested as ERD response was evaluated for use in the haptic feedback system. The goal of this study was to develop and test a human-robot interface that uses an ERD-based BCI to generate the FRVFs that facilitate the interface operation based on the user's movement intention.

2. METHODOLOGY

A. Participants and Materials

The intended target population will be children who have physical impairments; however, this preliminary study was done with two right-handed adults without disability, a 42 year old male and a 37 year old male. This was because the system was in the preliminary testing stage and still required careful validation of accessibility and safety before being used by our target population. The robotic system includes a Windows PC, an OpenBCI brain-computer interface (OpenBCI, Inc., Brooklyn, NY, USA), and a Novint Falcon haptic device (Novint Technologies, Inc., Albuquerque, NM, USA). The OpenBCI measured the user's brain signals over the motor cortex area and was used to discriminate movement intention during the robot operation. The Novint Falcon haptic robot device was used as the haptic user interface. The participants were asked to hold and operate the end-effector of the haptic robot device. A schematic diagram is shown in Figure 1.

LabVIEW (National Instruments, Corp, Austin, TX, USA) was used for the EEG data acquisition/analysis and robot control. In addition, the Statistics and Machine Learning Toolbox for MATLAB (MathWorks, Inc., Nadick, MA, USA) was used for design and validation of EEG classifiers based on the ERD response. All the features were implemented and run in LabVIEW for user experiments.

B. Experiments

The experiment was designed to discriminate between "rest" and "movement" states of the user's hand during robot operation and apply the FRVFs to the robot according to the user's detected motion intention. The experiment was divided into two sessions. During the first session, participants familiarized themselves with the experimental setup, and the system was calibrated for the individual. The participants were seated and asked to hold the end-effector of the haptic interface with their dominant hand. According to a visual cue displayed on the computer screen, the participants were asked to either rest or move the end-effector. The first session consisted of 30 trials. In each trial, a blank screen was displayed on the screen for the first 4 seconds. For the next 4 seconds, the visual cue indicating 'Movement' or 'Rest' was randomly displayed. At the same time, the participants were asked to move their respective limb according to the visual cue until the display was blank again. EEG brain signals were recorded during the trials and used to design a binary classifier between rest and movement for detecting the ERD response.

In the second session, feasibility of FRVFs based on the user's intention was investigated. The participants were seated and asked to hold the end-effector of the haptic device with their dominant hand as in the first session. First, the participants were asked to move the end-effector between the left and right endpoints of the robot workspace repeatedly 10 times with FRVF off in order to record the hand trajectories without FRVF. Next, with FRVF on, the participants performed 5 trials. In the trials with FRVF on, the participants waited during a blank screen for 4 seconds, and when a "Movement" visual cue occurred, the participants tried to move the end-effector from the left to the right endpoints of the robot workspace 10 times. If the user's ERD was correctly detected, the ERD-based FRVF was activated to block the user's hand from moving to the right half of the robot workspace as shown in Figure 2.

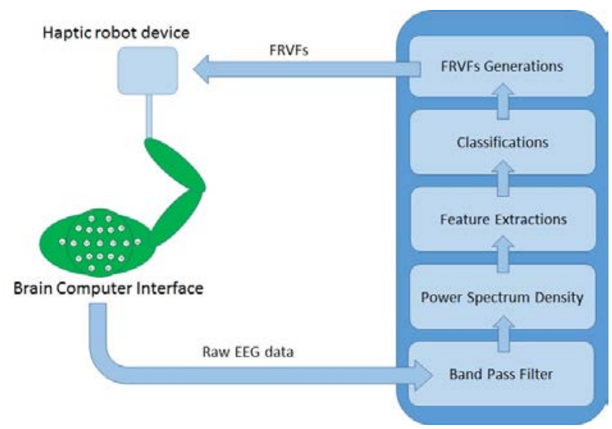

Figure 1. Schematic diagram of the proposed system

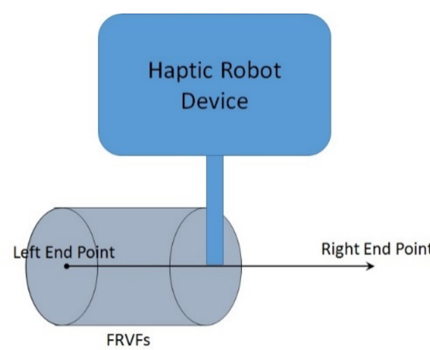

Figure 2. Illustration of the forbidden region virtual fixture (FRVF).

C. Haptic Device Control

The FRVF was added to the system as software-generated forces. The constrained region of motion was defined by a closed cylinder along the horizontal direction placed only on the left half of the robot workspace (Figure 2). There was no force applied to the haptic end-effector inside the cylindrical area, but there were forces applied if the user tried to move outside of the region. The FRVF was implemented as a nonlinear spring force attached between the current position of the robot's end-effector ($P_{end\ effector}$) and a reference point ($P_{reference}$) at each instant. If the distance between $P_{end\ effector}$ and $P_{reference}$ was greater than the cylinder radius, the FRVF was applied to the robot based on the following formula:

$$F_{VF} = \begin{cases} k * |distance|^3, if\ distance > radius \\ 0 \qquad\qquad\qquad , otherwise \end{cases} \tag{3}$$

where $distance = P_{reference} - P_{end\ effector}$ and k is the spring constant. The spring constant determines the amount of force applied; the larger the k value, the stiffer the boundaries of the cylinder. The k value in this study was set to 200 N/m.

D. EEG Data Collection and Analysis

The OpenBCI recorded two EEG channels over the motor cortex area in the left hemisphere, C3 and F3 locations of 10-20 system, at a sampling frequency of 250 Hz. The C3 and F3 locations were chosen because the ERD response is generally localized at the contralateral hand representation area, and the participants in this study were all right handed. The location of the electrodes used in this study is shown in Figure 3.

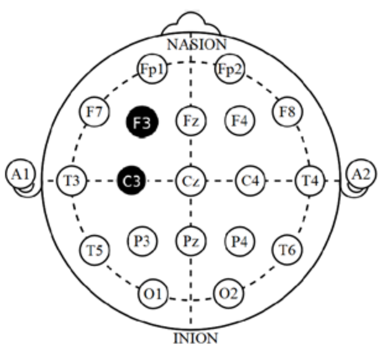

Figure 3. Locations of the electrodes used in the experiments (C3 and F3)

After a 3 - 40Hz FIR band pass filter removed noises, power spectral density using a hamming window was computed every 250 samples of EEG signals. The absolute power of alpha band (8-13 Hz) and beta band (14-26 Hz) of the EEG were extracted as the features in order to verify if the ERD response was present.

Two classification methods, Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) were used to discriminate the pattern of the EEG signals between "movement" and "rest". The accuracies of the classification for both methods were evaluated with 5-fold cross validation using MATLAB, and the classifier with the higher accuracy was chosen to be the classifier used in the second session for online classification.

3. RESULTS

The power spectral densities of the EEG data for the participants are shown in Figure 4. A significant decrease in alpha frequency band at C3 and F3 locations and small decrease in beta band at C3 location were observed. By using the 5-fold cross validations, LDA and QDA were examined for the classification accuracies of the ERD with different combinations of the features, which are the absolute power values of alpha and beta band at C3 and F3 locations, as shown in Figure 5. The LDA classifier demonstrated a higher classification accuracy than the QDA classifier overall, and the LDA with the combination of alpha band at C3 and beta band at C3 achieved the highest accuracy for both participants (69.2% for participant A and 62.6% for participant B). Therefore, the value of alpha band and beta band at C3 location were selected as the features for the LDA classifier used in the second session.

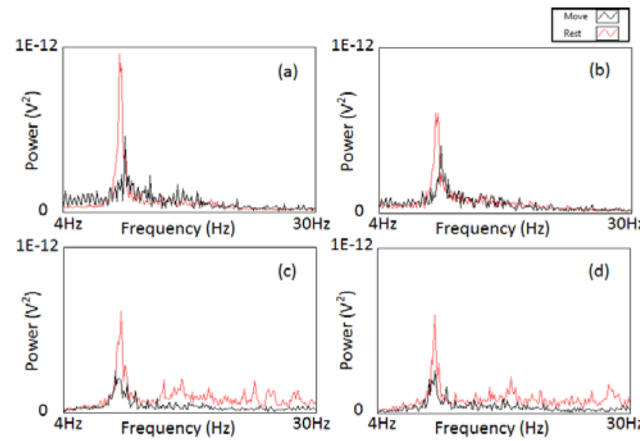

Figure 4. Power spectrum density of the EEG during movement (black line) and rest (red line) for the participants. (a) and (b) show the results of participant A at C3 and F3 locations respectively. (c) and (d) represent the results of participant B.

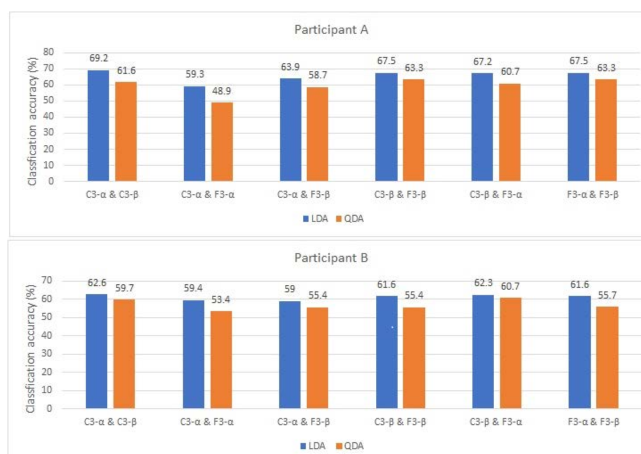

Figure 5. Classification accuracy of LDA and QDA with 5-fold cross validation.

Table 1 shows the number of times the virtual wall blocked hand motion to the right side of the robot workspace for each participant in each trial. The average of all trials for participant A and participant B were 7 and 6.4 out of 10 times respectively. The trajectory followed by participant A's hand without the ERD-based FRVFs and then with the ERD-based FRVFs in one trial is shown in Figure 6. Figure 6 (b) shows that the virtual wall blocked motion of the participant to the right side seven out of ten times. The trajectory in the X direction with respect to time in Figure 6 (b) also clearly shows that the virtual wall constrained the participant's motion and did not allow him to reach the right side of the robot workspace those seven times.

TABLE 1. THE RESULTS OF THE TRIALS IN THE SECOND SESSION.

		Participant A	**Participant B**
Trials	Total movements	Blocked movements	Blocked movements
1	10	6	7
2	10	6	7
3	10	7	5
4	10	7	7
5	10	9	6
Average	10	7	6.4

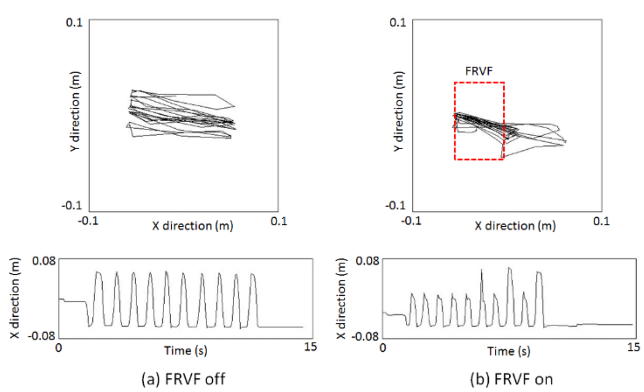

Figure 6. Hand trajectories during a trial in the second session. In (a), the results show how the user's hand moved during the trial in XY directions (Top) and in the X direction with respect to time (Bottom) without FRVF. In (b), the rectangle with a dashed border is the force field of FRVF. The hand trajectories during a trial with FRVF on are shown in (b).

4. DISCUSSION

The highest ERD classification accuracy obtained by the cross validations in this study was 69.4%. The results of this study demonstrated slightly lower classification accuracy than that of previous BCI studies [10-13]. Because of some inaccuracy in the ERD classification, the ERD-based FRVFs were not always successfully generated. Several possible reasons were considered to be a cause of the classification inaccuracy. First, artifacts caused by muscle activity could impact ERD classification, since EEG data collected in this study was not only EEG signals during motor imagery but also during physical movements. We used the FIR bandpass filter to remove noise from the environment before performing the classification process, but other than the FIR filter, applying a spatial filter such as Laplacian spatial filtering or Independent Component Analysis (ICA) with larger EEG channels may improve signal to noise ratio (SNR) of the EEG signals and may result in a better classification accuracy.

Secondly, inadequate feature selection used for the classifier design was considered to be another contributor to inaccurate classification. Even though power spectrum density is one of the common feature extraction approaches in the field of BCI, there are many other successful approaches, such as Discrete Wavelet Transformation (DWT). In this study, the frequency ranges used for the absolute power calculation were set to be a typical frequency range of alpha band, from 8 Hz to 13 Hz and beta band, from 14 to 26 Hz. However, the power spectrum of the EEG data in this study shown in the Figure 4 demonstrated that the amplitude of the signals between 9 Hz and 11 Hz constantly decreased during the user's movements. For this reason, the frequency range used for this study appeared to be too broad for the absolute power calculation. Narrowing the frequency range for the calculation will be expected to yield better classification accuracy.

For BCI applications, achieving high classification accuracy is always challenging [15]. Much BCI research has demonstrated results with higher ERD classification accuracy by conducting training prior to participation in trials. It is important to note that, in this study, no long-term training session was held prior to the start of trials due to the limited time schedule of the participants. Providing multiple sessions for BCI training prior to the trials would likely improve the BCI task performance in future trials. In addition, trials with more participants, including people with disabilities will be performed.

5. CONCLUSION

To the best of our knowledge, this is the first study to generate virtual fixtures based on a person's motion intention measured by ERD response. Even though the classification accuracy was only 69.4% and would need to be improved for practical use, the ERD response generated the FRVFs in real-time. This is an important step toward showing that ERD-based FRVFs can potentially be used for clinical populations in the future.

Decoding EEG allows us to understand the user's intention and translate the commands to devices without any physical movement required. Including different types of brain response (e.g., Event-Related Potential (ERP), and Steady-State Visual Evoked Potentials (SSVEP)), brain computer interfaces have potential benefits for people with severe physical impairments to express their intention. Combining other types of biological signals such as Electromyography (EMG) and Electrooculography (EOG) could also be possible approaches for robot control. EMG and EOG signals are generally of larger amplitude than the EEG and can be reliably observed in children with disabilities [16].

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