Integration of an Eye Gaze Interface and BCI with Biofeedback for Human-Robot Interaction

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Abstract - This paper presents an eye gaze and brain controlled interface, where eye gaze is used to select a target, and motor imagery is used to drive a mobile robot towards the target. Vibrotactile haptic feedback about where eye gaze is being tracked by the system and kinesthetic haptic feedback about the brain activity associated with movement intention was provided. The system was tested with five non-disabled adults and one individual with physical impairments. A robotic task to knock down a pile of blocks was performed with and without the haptic feedback, and the completion times of the task were compared. All six participants accomplished the robotic task with the haptic feedback faster than without it, and five participants thought that the task with the haptic feedback required less workload than the task without it. Haptic feedback can be a feasible component for eye gaze and brain controlled interfaces.

Keywords: eye tracker, eye gaze interface, brain-computer interface, human-robot interface

1. Introduction

The human-technology interface plays a fundamental role when controlling assistive technologies to perform functional activities [1]. Robots can be used as a means for children with physical impairments to perform functional play activities, and “human-robot interfaces” are used to access them. A common human-robot interface for people with impairments is a single button switch. This is the simplest type of interface and is essentially considered as a binary (on or off) device. Switches can be placed at different anatomical locations and made in different configurations depending on the user’s abilities. In Rios-Rincon, et al. [2] four children with severe cerebral palsy activated three single button switches for “forward”, “left turn”, and “right turn” of a mobile Lego robot.

Another common human-robot interface for people with disabilities is a joystick. Joysticks are often used in the field of assistive technology, for example, to control power wheelchairs [3]. In Song and Kim [4] a self-feeding robot for people with physical disabilities could be controlled by switches or a joystick, but the results of a usability evaluation indicated that the joystick was the preferred access method. The JACO arm (Kinova Rehab, Montreal, QC, Canada), which is designed specifically for people with limited or no upper limb mobility to achieve activities of their daily living, is sold with a joystick controller [5]. However, joysticks require a certain degree of physical ability to access and operate. To address this limitation, access pathways that do not require abilities to control body movement can be used.

As eye tracking has become more affordable and accessible it has been utilized for robot control applications. Eye tracking detects the user’s eye movement and determines the location on which the user is focusing [6]. Arai and Yajima [7] developed a feeding aid system consisting of a robot arm controlled with an eye gaze interface. A small camera was mounted on the tip of the robot end-effector, the view from which was displayed on a computer screen. The user gazed at the desired food on the screen and the robot brought the food close to their mouth so the users could eat it. In Encarnação, et al. [8], children controlled a mobile, car-like Lego robot with an eye gaze interface to participate in academic activities. Robot commands were displayed on a computer screen and children moved the robot by fixating their gaze on the desired movement command.

Brain-controlled access pathways, often referred to as a brain-computer interfaces (BCI), have been emerging as a new way to control devices in recent years [9]. Electroencephalography (EEG) is a non-invasive method to record the brain's activity with electrodes placed on the surface of the scalp [10]. EEG can be used to detect the brain activity associated with real or imagined movement, which produces changes in the sensorimotor rhythms. Real or imagined motor behaviour leads to a decrease of spectral amplitudes of alpha rhythm in the range from 8 to 13 Hz, known as Event-Related Desynchronization (ERD), and an increase of spectral amplitudes of beta rhythm in the range from 13 to 26 Hz, known as Event-Related Synchronization (ERS) [11]. The signals can be detected and classified as rest, physical movement, or motor imagery using machine learning methods, and then used to control technology. Huang, et al. [12] tested BCIs for 2-dimensional cursor control based on ERD and ERS during motor execution and motor imagery with five participants without impairments. In

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Cincotti, et al. [13], 14 participants without impairments and 14 participants with spinal muscular atrophy or Duchenne muscular dystrophy successfully performed 2-dimensional cursor control and mobile robot control with their ERD response.

Eye gaze and BCI have been integrated to control robots. For example, Frisoli, et al. [14] developed a gaze and ERD-based BCI controller for an exoskeleton for stroke rehabilitation to assist the movement of the upper limb in reaching. The eyes looked in the direction to go, and the ERD made the exoskeleton move to reach a target. An integrated system such as this could be a solution for children with severe physical impairments to control assistive robots for play: they can select a desired toy or robot destination by looking at it, and move the robot towards it using the BCI.

In order to use such a system to control a robot in a physical environment, the mode of feedback needs to be addressed. With eye tracking, it is important for the user to receive feedback about where the tracker is interpreting the gaze in order to support successful gaze interaction. If used for robot control, users typically are required to look at a screen to select a robot command and then look at the robot to check the effect of the command. However, this forces the user to keep changing their visual attention during the robot control and adds a layer of complexity [8]. An alternative to visual feedback is needed, for instance, vibrotactile haptic feedback, which has been used to enhance the performance of on-screen gaze interaction [15] and off-screen interaction [16].

BCI using ERD/ERS has the advantage of not needing a stimulus as in other BCI applications do (e.g., an array of options on a screen for the P300 or indicators flashing at frequencies for Steady-State Visual Evoked Potentials); however, the classification accuracy of ERD/ERS is usually lower than those stimulus protocols. Increasing the classification accuracy of the user's movement intention when using BCI is a crucial challenge for reliable device control. Sakamaki [17] investigated the effect on classification accuracy of an ERD/ERS-based BCI system with feedback in the form of passive movement of the hand provided by a haptic robot interface. The classification accuracy using the system with this kinesthetic haptic feedback was significantly higher than that using only motor imagery. Thus, kinesthetic haptic feedback may be effective in helping move a robot towards a target more effectively.

The main objective of this study was to develop and test an integrated eye gaze and BCI-based human-robot interface providing vibrotactile haptic feedback for eye gaze to select targets and kinesthetic haptic feedback for motor imagery for robot control. The research questions were:

- Can haptic feedback (vibrotactile haptic feedback for eye gaze and kinesthetic haptic feedback for motor imagery) from the integrated eye gaze and BCI-based human-robot interface make a functional robot task faster?
- Can haptic feedback lead to a lower workload in the functional robot task compared to without it?

2. Methods

2.1 Participants

The sample included five male adults without a disability (P1 – P5), aged from 22 to 38 years (mean 28 ±7.8 years). The system was also tested by a 52-year-old female with quadriplegic cerebral palsy (AD1) who has been classified as Level IV in the Gross Motor Function Classification System Expanded and Revised (GMFCS-E&R) [18], and Level III according to the Manual Ability Classification System (MACS) [19], meaning she uses power mobility and has difficulty handling objects. Participant AD1 is also affected by strabismus and has difficulty focusing on objects with both eyes simultaneously. All the participants had prior eye tracking and BCI experience from previous studies. Ethical approval was received from the local Health Research Ethics Board at the University of Alberta.

2.2 Experimental Setup

The experimental setup of this study consisted of four components, a mobile robot, an eye tracking system, a BCI system, and a haptic feedback system as shown in Figure 1. A picture of the whole system is shown in Figure 2. Details of each component are described below.

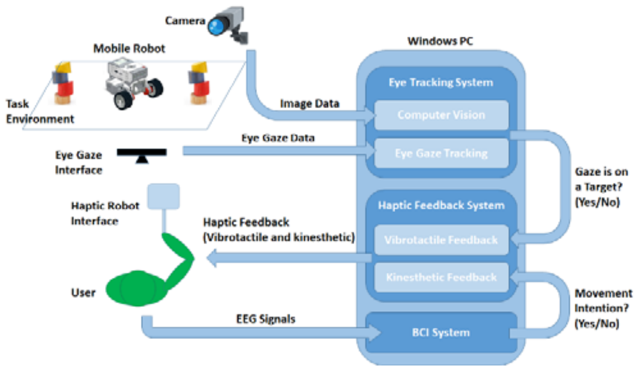

Fig. 1 Schematic diagram of the system in interaction with the user and the task environment.

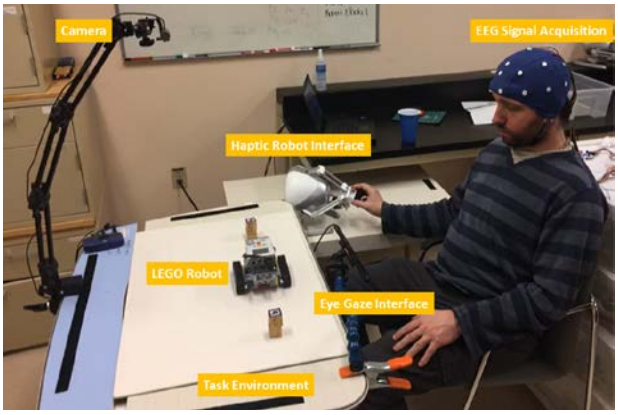

Fig. 2 Picture of the system with the human-robot interface and the task environment.

2.2.1 *Mobile Robot*

The mobile robot used in the study was a Lego Mindstorms NXT (LEGO System A/S, Billund, Denmark), which connected with a PC wirelessly via Bluetooth. The Lego robot was placed between two piles of wooden blocks (see Figure 1 and Figure 2), and the task was to select the pile of blocks to knock over using eye gaze and then move the Lego robot towards it using motor imagery until it knocked down the pile.

2.2.2 *Eye Tracking System*

A licensed Tobii eye tracker 4C (Tobii Technology, Danderyd, Sweden) was used as an eye tracking interface to detect the location of the participant's eye gaze in the task environment. Additionally, a USB camera (Dynex, Richfield, MN, USA) was mounted over the task environment to acquire the image data of the task environment. Since the eye tracker is designed to be used on a two-dimensional screen, the participant's gaze was mapped into the two-dimensional plane of the task environment by using a projective homogeneous transformation, called a homography as shown in Figure 3. The 3 x 3 homogeneous transformation matrix was obtained by solving the following linear equation [20]:

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \quad (1)$$

where $[x \quad y \quad 1]^T$ represents the gaze position data when the participant is looking at a calibration point and $[x \quad y \quad 1]^T$ represents the location of the calibration point captured by the USB camera.

To calibrate the system, a template on which four calibration points were printed was placed in the task environment, and the USB camera captured the template image and detected the position of the calibration points. The participant then fixated their gaze at each calibration point in turn, and the homogeneous transformation matrix was calculated using equation (1).

The piles of blocks in the task environment were detected by an object recognition program coded in LabVIEW (National Instruments, Austin, TX, USA), and the locations were obtained. When the participants wanted to select a target in the task environment, they needed to fixate their gaze on the target for a dwell time that was set to 1.5 seconds in all the conditions. A typical dwell time for the gaze fixation is 0.5 to 1 seconds [21], but 1.5 seconds was selected in this study based on pilot testing of the system. If the participant's gaze came off the target before 1.5 seconds and then back on the target, counting of the dwell time started over again.

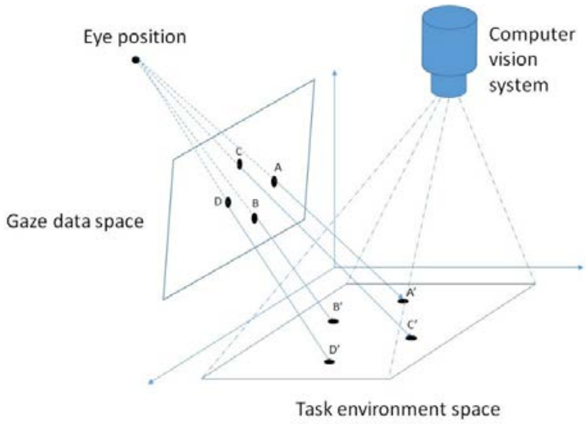

Fig. 3 Points in the eye tracker space and environment frames, which were related by a transformation.

2.2.3 *Brain-Computer Interface (BCI) System*

The BCI system included OpenBCI hardware (OpenBCI, Inc., Brooklyn, NY, USA) and OpenViBE software [22]. OpenBCI was used to detect the participant's EEG signals. OpenViBE is an open source graphical programming software, which is suited to numerous BCI applications, such as a P300 speller or SSVEP-based BCI control, but for this study, it was employed with motor imagery. Eight EEG channels over the pre-motor cortex of the brain, which is responsible for motor-related activities, were recorded at a sampling frequency of 250 Hz (i.e., Cz, Cp, F3, C3, P3, F4, C4 and P4 of the international 10-20 system). The reference and bias channels were, respectively, T7 and T8. After performing a 60 Hz notch filter for noise removal and a 7 to 30 Hz FIR band-pass filter to acquire the sensorimotor components of the EEG signals, a Common Spatial Pattern (CSP) filter was applied to the signals to extract the feature vector of the movement intentions. CSP is a mathematical procedure used in signal processing for separating a multivariate signal into additive subcomponents, which have maximum differences in variance across two windows [23]. The logarithmic power of the feature vectors extracted by the CSP filter was then employed as the input of a Linear Discriminant Analysis

(LDA) classifier to discriminate between the participant's movement intentions of MOVE or REST. LDA was selected as the BCI classifier for this study as preliminary experiments demonstrated that it could offer better BCI classification accuracy in comparison to other classification methods such as linear Support Vector Machine and Multilayer Perceptron [24].

2.2.4 Haptic Feedback System

There were two types of haptic feedback provided through the interface to the participants as biofeedback during the experiment. Vibrotactile haptic feedback was used to inform the participants about their gaze location and to help them sustain their gaze on the target. A 100 Hz sine wave was generated using a USB stereo sound adapter, which was then sent to an amplifier to drive a vibration motor (Bit Trade One, Kanagawa, Japan). The motor was attached to the user interface of a Novint Falcon haptic robot (Novint Technologies, Inc., Albuquerque, NM, USA), which allowed the motor to be in contact with the participant's hand when they were holding the interface. When the participant's gaze was within a radius of 4.5 cm from the center point of the target, the vibrotactile haptic feedback began. This radius was chosen based on a pre-test to minimize the error of target selection. The intensity of the feedback increased proportionately with the length of time the participant's gaze was fixed on the object, to notify them of how the dwell time was progressing.

The Novint Falcon haptic robot interface was used to provide kinesthetic haptic feedback about the EEG signals by moving the participant's hand, which was placed on top of the user interface. The movement of the robot was based on the confidence values of the BCI classification of the movement intentions. The confidence of the classification results for the movement intention was calculated in a range from 0 to 1. When the confidence values were closer to 0 these matched the classification of REST, and when the confidence values were closer to 1 these matched to the classification of MOVE. If the confidence value of the BCI classifier was in excess of 0.6, the haptic robot interface started to move the participant's hand, which was placed lightly on top of the interface. The force exerted on the haptic robot interface by the participants' hand was measured to ensure that they were moving it by their EEG motor imagery, not physically pushing the interface. If an interaction force over 4 N was detected on the interface, the EEG data during that period was excluded. In this study, only 1.8 % of the data needed to be excluded.

2.3 Procedures

The participant sat approximately 60 cm away from the eye tracker, which was placed in front of the task environment. The haptic robot interface was located beside the participant so that it could easily be reached with whichever hand was dominant, and the EEG electrode cap was placed on the participant's head.

First, BCI classifier training was performed in order to design the classifier to discriminate the movement intention of the participant. A modified version of the Graz BCI training protocol was used [25]. As BCI training based on motor imagery is regarded as tedious and time-consuming, in order to make the training more motivating and sustain participants' attention, the protocol was modified to a game-like scenario, as in a paper by Sakamaki [17].

During the BCI training, a car displayed on the computer screen moved or stopped according to the traffic light on the screen (see Figure 4). The task cues for the traffic light were STOP, READY, and MOVE. The training was performed with two different task conditions: without and with the kinesthetic haptic feedback. For the task without the haptic feedback, the participant's hands rested in their lap during the training. When the traffic light indicated MOVE, the car began to drive from the right to the left. During this period, the participants were instructed to imagine their arm moving from right to left. When the traffic light indicated STOP the car did not move, and the participants were instructed to imagine no movement. For the task with the kinesthetic haptic feedback condition, the participants held the end effector of the Novint Falcon haptic robot interface during the training. The task was the same as the without the haptic feedback condition, however, the haptic robot interface facilitated the participant's hand movement from right to left simultaneously with the movement of the car.

Fig. 4 Graphical user interface for the BCI training

After the training, the participant's eye gaze was mapped to the task environment using the calibration procedure described above. The task steps were as follows: 1) The researcher gave verbal instructions to the participant about which pile of the blocks to knock down (a random order was calculated prior to the experiment); 2) The participant fixated their gaze at the target block and when the system determined that the participant's gaze was on a target for more than the 1.5 second dwell time, a computerized voice confirmation was given to the participant (i.e., "left target was selected" or "right target was selected"); 3) The participant then imagined moving their dominant hand to drive the Lego robot until the target block was knocked down.

The task was done with and without vibrotactile and kinesthetic haptic feedback. For the task without the haptic feedback, the participant's hands rested in their lap, and no feedback was provided selecting the target or moving the robot. For the task with the haptic feedback, the participant held the haptic robot interface with the dominant hand, so that the participant could receive the vibrotactile haptic feedback during target selection and the kinesthetic haptic feedback during motor imagery. Ten trials were performed by each participant in each task condition. To avoid bias from a learning effect, the order of the task condition was counterbalanced across the participants. The task timed out when the participant could not select a target and knock down the blocks within 20 seconds. This occurred in 19% of the trials.

2.4 Measurements and Analysis

The following were measured in with and without the haptic feedback conditions:

- **BCI classification accuracy during training:** The classification accuracy of the LDA classifier for MOVE and REST based on EEG signals acquired in the BCI training was calculated using 5-fold cross-validation.
- **Overall task and subtask completion times (measured in milliseconds): Overall time** was measured from the task cue until the robot knocked down the blocks. **Target selection time** was the time to select the target using eye gaze (from the task cue until the target selection was made) and **Robot driving time** was the time from the robot started to move until the blocks were knocked down with it.
- **NASA-TLX score:** The NASA Task Load Index (NASA-TLX) was used to analyze subjective mental workload in six different aspects: Mental Demand, Physical Demand, Temporal Demand, Own Performance, Effort, and Frustration Level. The participants were asked to rate the workload of the system using scales of 0 to 20 on each workload aspect, and the total score of the workload was also obtained.

For the overall task and subtask completion times within subject paired comparisons with a 95% confidence level were made to analyze the effect of the haptic feedback on the robot control task by using a paired-samples t-test when the normality assumption was met and the Wilcoxon signed-rank test when it was not. Descriptive statistics were used for BCI classification accuracy and NASA-TLX. Participant's related comments were transcribed.

3. Results

3.1 BCI Classification Accuracy during Training

Table 1 shows the BCI classification accuracy of the LDA classifier for each participant during the BCI training. Four participants, P1, P2, P5, and AD1 showed higher classification accuracy with the kinesthetic haptic feedback while two participants, P3 and P4, showed higher classification accuracy without it. The average classification accuracy with the kinesthetic haptic feedback for participants without impairments (70.18%) was similar to the average accuracy without the haptic feedback (69.37%). For AD1, the classification accuracy without the haptic feedback was lower than the average for the participants without impairments, and her accuracy with the kinesthetic haptic feedback was the second highest among all the participants.

TABLE I

BCI CLASSIFICATION ACCURACY FOR ALL THE PARTICIPANTS

Subject	Accuracy without haptic feedback (%)	Accuracy with kinesthetic haptic feedback (%)
P1	58.46	72.04
P2	70.62	78.95
P3	75.30	57.79
P4	80.20	65.49
P5	66.36	72.56
AD1	60.34	78.14

3.2 Overall Task and Subtask Completion Times

Figure 5 shows the overall task completion time of all the six participants. All the participants achieved the task with the haptic feedback (i.e., vibrotactile for eye gaze and kinesthetic for motor imagery) faster than without it. Two participants, P2 and P5, completed the task with the haptic feedback significantly faster than without it ($p=0.01$ for P2 and $p=0.01$ for P5). The overall task completion time for the adult participant with physical impairments, AD1 was the longest time among all the participants for both of the task conditions.

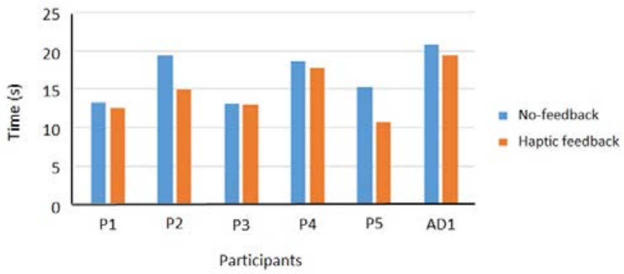

Fig. 5 Overall Task completion time with the different task conditions for all the participants

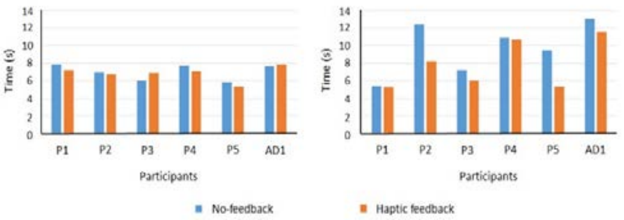

Fig. 6 Target selection time (left) and the robot driving time (right) with the different conditions for all the participants

For the target selection time, no significant difference between the two conditions was found for any participant. Four participants, P1, P2, P4, and P5, selected the target faster when the vibrotactile haptic feedback was provided, while two participants, P3 and AD1, selected the target faster without the haptic feedback as shown in Figure 6 (left), but the differences were small, and none of them were significant. The average target selection time for the participants without impairments was 6.87 ± (2.63) seconds for the task without the haptic feedback and 6.64 ± (0.94) seconds for the task with the vibrotactile haptic feedback.

Regarding the robot driving time, all the participants had a faster time reaching the target when the kinesthetic haptic feedback was on. Participants P2 and P5 had a significantly shorter time for the robot to reach the target when the kinesthetic haptic feedback was provided ($p=0.01$ for P2 and $p=0.01$ for P5). AD1 had the longest time to drive the robot among all the participants (see Figure 6 (right)) but achieved the task faster with the kinesthetic haptic feedback than without it. The average robot driving time for the participants without impairments was 9.07 ± (4.38) seconds for the task without the haptic feedback and 7.09 ± (3.64) seconds for the task with the kinesthetic haptic feedback.

3.3 NASA-TLX

Each participant's total score on all the six aspects of the NASA-TLX (120 points maximum) is summarized in Figure 7. The average score for the task without the haptic feedback was 57.67 points and for the task with the haptic feedback, it was 48.67 points. The workload of the task with the haptic feedback was rated lower by all participants except P3. Participants commented that it was easier with the haptic feedback because the vibrotactile feedback helped them know when their gaze was located on the target and the kinesthetic haptic feedback helped them know how well they were performing motor imagery. On the other hand, some participants commented that the haptic feedback was stressful when it did not behave exactly as they intended. P3 commented that it was hard to concentrate on driving the robot when his hand and the haptic robotic interface came into his field of vision.

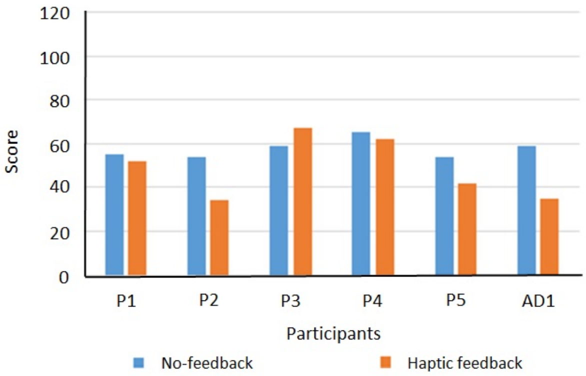

Fig. 7 Total score of the NASA-TLX ask with the different task conditions for all the participants

4. Discussion

The overall task times using the proposed human-robot interface was faster with the haptic feedback than without it by all the adult participants without impairments, with two of them showing significance. More participants demonstrated a faster target selection time using eye gaze with the vibrotactile haptic feedback than without it; thus, the feedback could have played a role in helping the participants to fixate their gaze. However, the difference in the target selection time between the two conditions was not significant, likely because there were only two targets and the radius of 4.5 cm for the gaze target acceptance size was relatively large, making it easy to select. If there were more targets in the task environment, the acceptance size would have to be smaller to avoid selecting the wrong target, and in that case, vibrotactile haptic feedback might have been more helpful to attain the smaller targets. This was the case in Sakamaki, et al. [16] where targets of 3cm led to significant differences between without and with vibrotactile feedback. For the adult participant with physical impairments, AD1, her strabismus may have caused the inaccuracy in her gaze interaction. However, her results indicated that the 4.5 cm target acceptance size allowed her to perform the target selection using the gaze fixation in a comparable way to the participants without impairments with or without feedback.

Regarding driving the robot with motor imagery, all the participants were able to drive the robot and knock down the target blocks faster in the task with the kinesthetic haptic feedback than without it, although the difference was only statistically significant for two participants. A difference was expected based on the study by Gomez-Rodriguez, et al. [26] who found the sensorimotor rhythm could be induced by passive movement. In their study participants performed a motor imagery-based BCI task with significantly higher classification accuracy than visual feedback. It is to be noted that some confounding brain activation may have been elicited when participants supported their arm against gravity while holding the user interface of the Novint Falcon. Therefore, the brain activities collected in the kinesthetic haptic feedback condition may not be purely brain activities associated with imagined arm movement and sensory motor patterns induced by the kinesthetic motion of the Novint user interface.

Almost all of the participants reported that the task with the haptic feedback required a lesser workload than the task without the haptic feedback. The larger score differences in the NASA-TLX for P2, P5, and AD1 between the two task conditions compared to the difference for P1, P3, and P4 could be related to task completion time: P2 and P5 were significantly faster, and AD1 was somewhat faster, with the feedback. Only P3 rated the task with the haptic feedback as requiring a greater workload than that without feedback. His difficulty concentrating when he could see his hand move could be addressed by blocking the view of his hand during the task or locating the haptic feedback robot interface out of his sightline.

5. Conclusion

In this study, two natural physiological functions were used to accomplish a simple mobile robot control task; eye gaze for target selection was integrated with motor imagery-based BCI for robot control and the effectiveness of feedback was evaluated. Vibrotactile feedback for eye gaze and kinesthetic feedback for motor imagery improved participants' performance. The difference in time between with and without feedback for target selection with eye gaze was small, however, the difference in time for driving the robot using motor imagery was larger, with results for two participants showing a significant difference. It is a technical challenge to overcome the low accuracy of gaze interaction in a physical environment or BCI classification accuracy to achieve reliable robot operation (compensating for movement artifact and signal noise). However, haptic-based biofeedback could improve the control over the participant's physiological activity, and thus enhance their performance in robot control tasks. It is also worth mentioning that the positive effect of our proposed human-robot interface with feedback was useful not only for most participants without impairments but also for the adult participant with physical impairments, but the results might be different with other participants.

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