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Examination of effectiveness of kinaesthetic haptic feedback for motor imagery-based brain-computer interface training

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ABSTRACT

Motor imagery-based brain computer interfaces (BCI) performance can be reinforced by visual presentation of feedback about the motor imagery displayed on a screen. However, to directly control robots by the BCI, a different feedback modality may be preferred. The objective of this study was to develop a BCI with kinaesthetic haptic feedback based on the detected motor imagery, and compare its performance to using visual feedback. Twelve online BCI runs with both feedback modalities were performed by ten adults without impairments, and four runs in a game-like task were performed by one adult with cerebral palsy and one child without impair-ments. The participants completed the BCI training with an average accuracy of 67.28 ± 11.2% for visual feedback and 75.12 ± 12.3% for kinaesthetic haptic feedback. The BCI training with kinaes-thetic haptic feedback resulted in less workload and statistically higher classification accuracy than visual feedback (p = 0.03).

1. Introduction

Play represents a critical activity for development when children explore their environment by manipulating objects within it [1]. Manipulative play contributes to a child's development of motor, social, linguistic, and cognitive skills, and it also stimulates creativity, learning, mastery, self-expression, and adaption [2]. However, children who have physical disabilities may find it difficult to participate in certain play activities as a result of impairments that affect movement, grasping, and reaching out for objects. They may tend to watch others playing rather than participating themselves because their playmates more effectively or frequently handle the play objects [3]. This can impede their development across multiple areas [4].

Robots, such as a mobile Lego Mindstorms robot [5] and the workstation Play-ROB [6], have enabled children who have physical impairments to manipulate toys [7]. The children used switches to control the Lego robots [5] and a joystick to control the Play-ROB [6]. However, these interfaces are not useable by children who have significant physical impairments. Brain-computer interfaces (BCI) are a potential solution for children with severe physical impairments, as they do not require motor movement, and they have been used, primarily by adults, to control computer applications, and control devices such as robots or neuroprostheses [8,9].

In order for children with disabilities to use a BCI to control mobile robots, we must try to make the system easy to set up and use. Noninvasive electroencephalography (EEG) is appropriate since it records the brain's activity through electrodes on the surface of the scalp [10]. Using a self-induced motor imagery paradigm, rather than external stimuli presented on a computer screen, is preferable since attending to both the robot in the physical environment and a screen to pick a desired option using eye-gaze has been shown to be challenging for children [11]. Specifically, we propose to use event-related desynchronization/synchronization (ERD/ERS), which detects decreases in alpha rhythm from eight to 13 Hz (ERD) [12], and increases of beta rhythm from 13 to 26 Hz (ERS) [13].

One drawback of motor imagery paradigms is the training required to achieve sufficient accuracy to use it functionally. 14,estimated that between 15% and 30% of the non-disabled population cannot produce the ERD/ERS to control a BCI in their first session. It is recommended to perform repeated practice with feedback to acquire the skill to control the BCI system [15]. One of the most widely used BCI training protocols in the field of BCI research is the Graz training protocol [16]. Following a cued stimulus such as visual signs or symbols indicating when a user should perform motor imagery or rest, the induced sensorimotor rhythms are detected and classified according to the probability that the user is imagining movement or resting, and the user receives visual feedback on a computer screen in order to see the strength of their ERD/ERS brain response [15]. However, in order to use the BCI to control a robot in a physical play environment without a screen, we will need to examine the use of a different feedback modality.

Several studies involving participants with physical impairments have used ERD/ERS to control assistive technology [17–19]. In 17, 14 participants without impairments and 14 participants with spinal muscular atrophy or Duchenne muscular dystrophy successfully performed two-dimensional cursor control with motor imagery. The average classification accuracy achieved was 80% for participants without impairments and 62% for participants with impairments. A study by 19,evaluated the ERD/ERS of six participants without impairments and three participants with spinal cord injury (SCI) during upper limb movement activities. The BCI system correctly detected 75% of the movements for participants without impairments, and the detection rates for participants with SCI was similar to those of the participants without impairments.

There is a lack of BCI implementation for children, and particularly for children with severe disabilities [20–22]. The frequency of mu rhythms in children is less than in adults and varies depending on age [23], but there have been studies of ERD/ERS with children. 24,investigated the feasibility and test-retest reliability of the ERD by using a brain mapping system with five non-disabled child participants and seven child participants with cerebral palsy. ERD during reach-and-grasp hand movements were repeatedly measured and obtained excellent reliability with a level of significance ($p < 0.05$) for both participant groups. Other studies have used motor imagery with children, but using proprietary software from the BCI headset company, for example, children with cerebral palsy played computer puzzle games [25] and children without disabilities controlled a toy car [26]. No accuracy results were reported.

Auditory or haptic feedback can also be used with BCIs [27]. Haptic feedback can be tactile or kinaesthetic sensations: tactile sensation is normally conveyed through the skin, such as by pressure or vibrations, while kinaesthetic sensation refers to static and dynamic posture based on muscles and tendons that allow us to feel the pose of our body, i.e. proprioception [28]. A review of feedback modalities in BCI revealed 19 studies where visual, auditory, tactile, and proprioceptive feedback were compared to at least one other modality [29]. Seventeen out of the 19 studies used motor imagery-based BCI. Visual feedback was included in every study, seeing as it was intrinsic to the tasks (e.g. seeing the control item move, such as the cursor on the screen). Two out of the five studies comparing auditory feedback found that it was effective. The effect of tactile feedback for motor imagery-based BCI tasks seemed to be inconclusive, where studies had either a better response, or the same as the control. In one application with a neuroprostheses, the vibrotactile feedback made it hard to concentrate [30], but in another study there were improvements in performance reading a map, which were attributed to freeing up the visual channel [31]. Others have found that performance will vary among participants in studies comparing vibrotactile feedback with visual and auditory feedback in a motor imagery task [32]. However, the 29,review found that proprioceptive feedback was effective in four out of four studies, all of which were testing proprioceptive feedback combined with visual feedback in neuroprosthetics. Notably, only 10.5% of the 19 reviewed studies involved individuals with disabilities.

Another review specifically examined haptic technologies in BCI/neurofeedback applications [33]. The ERD/ERS was the most popular motor imagery paradigm, and haptic feedback was usually done in conjunction with visual feedback. They pointed out that even though the first study of haptic feedback in clinical applications was with an individual with a high spinal cord injury [34], the vast majority of studies use kinaesthetic feedback for rehabilitation of stroke patients. The most common interfaces were orthoses placed on the hand or arm. The review stated that several studies seem to indicate that haptic feedback is either equivalent to, or more effective than, visual feedback in certain applications, and they called for further studies.

Passive movements can induce EEG patterns similar to those observed during motor imagery [35], so studies have used kinaesthetic feedback to help induce sensorimotor rhythms for better performance. For example, non-disabled participants used kinaesthetic feedback through a haptics-enabled robot for rehabilitation therapy [36] and non-disabled participants received feedback through an orthosis attached to the right hand [37]. Both studies saw enhanced performance, even though there was only a single session.

In the current study, a BCI system and training protocol were designed that provided kinaesthetic haptic feedback according to the detected movement intention to examine if this phenomenon could benefit classification accuracy compared to typical visual feedback. Additionally, the feedback was examined over several sets of BCI training to see if accuracy would improve.

In developing technology for individuals with disabilities, it is common to first test with individuals without disabilities to examine if expected outcomes occur and determine challenges with the use of the technology [38–40]. As such, Study 1 was performed with adults without disabilities who tested both visual and haptic feedback to examine if the latter might provide some benefit in BCI training. After adjustments to the experimental set up and procedure, Study 2 was performed with a child without impairment and an adult with cerebral palsy in case studies to examine effects with populations closer to our target group. The research questions of the studies were:

(1) Which feedback modality (visual or kinaesthetic haptic) leads to better BCI classification accuracy?
(2) Can repeated runs of the BCI training with the feedback improve the BCI classification accuracy over time?
(3) How does power spectrum density of alpha and beta bands differ between a motor imagery task with visual feedback and haptic feedback?
(4) Which feedback modality leads to a lower workload for the participants?

2. Methods: Study 1

2.1. Study design

A crossover study design was used where each participant performed the BCI training in two conditions, with visual feedback and with kinaesthetic haptic feedback. To account for practice effects, the order of the feedback conditions was counterbalanced across the participants. Ethical approval was received from the local Health Research Ethics Board Health Panel at the University of Alberta.

2.2. Participants

Ten university students without physical disabilities, six males and four females, aged from 22 to 38 years (mean 28 years, standard deviation 4.3 years), participated in the study. The participants were all right-handed and had no prior BCI experience.

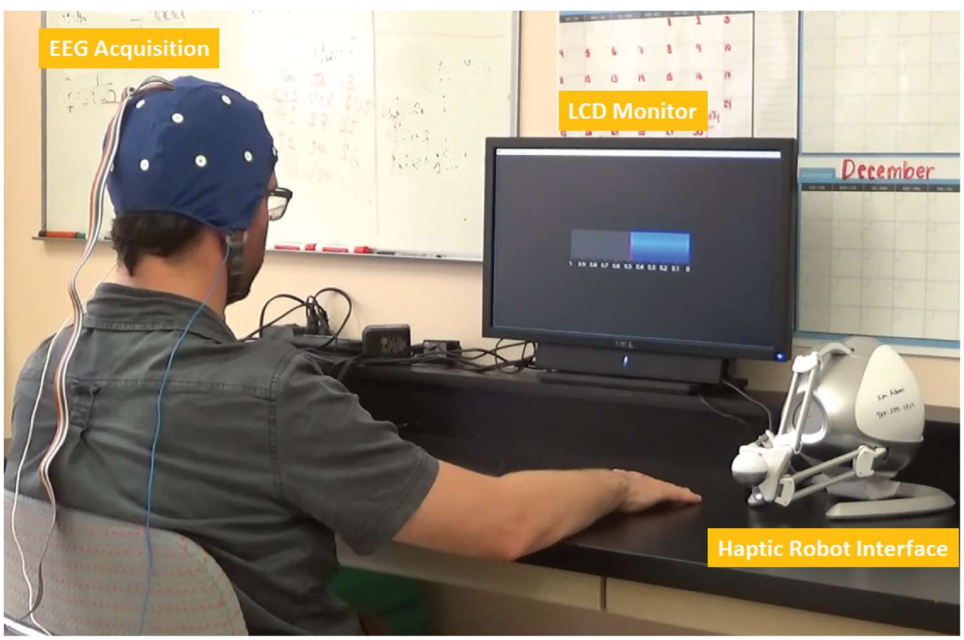

Figure 1. Picture of the BCI training system.

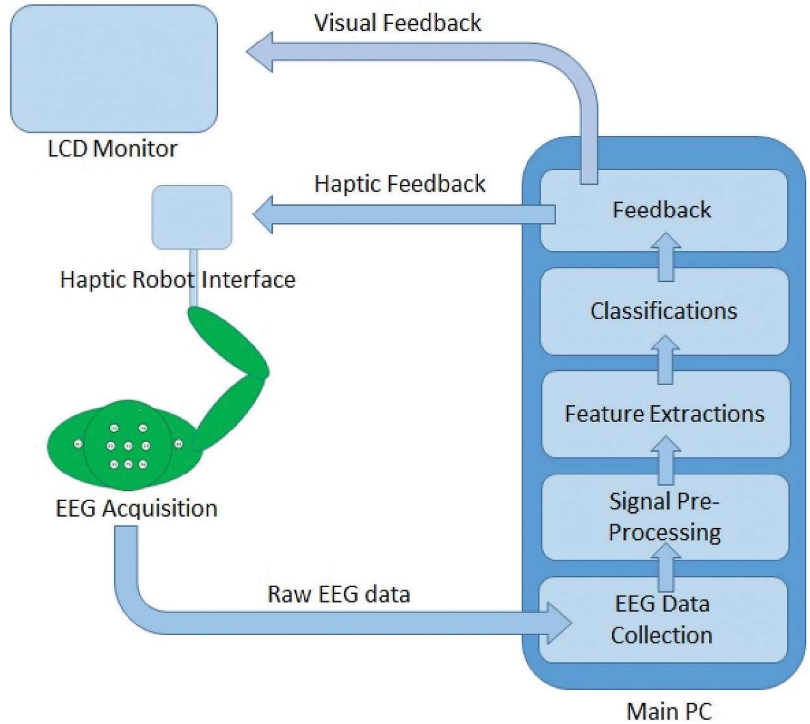

Figure 2. Schematic diagram of the BCI system.

2.3. Experimental setup

An EEG acquisition hardware device called OpenBCI (OpenBCI, Inc., Brooklyn, NY, USA), an open source BCI software called OpenViBE [41], and a graphical programming language called LabVIEW (National Instruments, Corp, Austin, TX, USA) were used for the BCI system. The system was composed of five modules: EEG data collection, signal pre-processing, feature extraction, classification, and feedback. A 19 inch LCD monitor was used to display the visual feedback, and a Novint Falcon (Novint Technologies, Inc., Albuquerque, NM, USA) was used to give the kinaesthetic haptic feedback. A picture of the system is shown in Figure 1, and a schematic diagram of the system is shown in Figure 2.

EEG Data Collection: An EEG cap with eight electrodes was placed on the surface of the participant's scalp to collect EEG signals, which were sampled with a 250 Hz sampling frequency. The input bias current of the BCI system was about 6 nA, and the impedance of all electrodes was kept below 5 kΩ. Channels Cz, Cp, F3, C3, P3, F4, C4 and P4, according to the 10–20 international system, were selected since they are over the premotor cortex area of the brain, which is responsible for the motor imagery and physical movement of the upper limbs. Channels T7 and T8 were used as reference and bias of the BCI system, respectively.

Signal Pre-processing: The collected EEG data was preprocessed in real-time through a notch filter with cutoff frequencies between 58 and 62 Hz to reject power line noise. Then, the signal was band-pass filtered from seven to 30 Hz to preserve the alpha and beta bands [36,42,43].

Feature Extraction: In order to retrieve the component signal that best represented the brain activity for the motor imagery task from the pre-processed signal, a Common Spatial Pattern (CSP) filter was applied in the feature extraction module [44]. CSP, a highly successful method for ERD/ERS detection, is a mathematical procedure used in signal processing for separating a multivariate signal into additive subcomponents which have maximum differences in variance between two windows [45]. The EEG signals were spatially filtered using CSP and the logarithmic band powers of the filtered signals were then sent to the classification module. One-second epochs were sent to a classifier every 0.0625 seconds.

Classification: Linear Discriminant Analysis (LDA) was used for the BCI classification (i.e. MOVE or REST) because it achieved better BCI classification accuracy than linear Support Vector Machine (SVM) and Multilayer Perceptron (MLP) with participants without impairments in a previous study [46]. After the data was classified using the LDA, the control loop was closed with the feedback, as follows.

Visual Feedback: The visual feedback was provided to the users through the computer screen as visual stimuli. A bar indicator displayed on the computer screen presented the confidence values of the classification when the participants were performing the motor imagery task (i.e. thinking about moving the dominant hand from right to left across the midline, called MOVE, or thinking about resting the dominant hand, called REST). The confidence of the classification results for the motor imagery was obtained by an OpenViBE feature called Classification Processor, which estimates posterior probability of the LDA based on Bayes' theorem. Smaller confidence values corresponded to the classification of REST while larger confidence values corresponded to the classification of MOVE. The value was in the range of zero to one, and the threshold of the classification between REST and MOVE was 0.5.

Kinaesthetic Haptic Feedback: Kinaesthetic haptic feedback, i.e. passive movement of the participant's hand based on the sensorimotor rhythm brain response, was given using the Novint Falcon haptic robot interface. When the confidence value of the classifier exceeded 0.6, the haptic robot interface started to move the participant's hand from the right to left endpoints of the robot workspace. The classifier threshold of 0.6 was chosen according to pretesting to make sure that the haptic interface only moved when it was supposed to, so it would not confuse the user during the online run.

2.4. Procedures

Each participant performed six sessions for each feedback modality. Sessions were approximately one hour each, including system setup, BCI classifier training and online runs. The participants performed the sessions for the first feedback condition within two weeks and had at least a one-week resting period before doing the next feedback condition, the sessions of which were completed within two weeks. Each session had one training BCI run (that is, training of the classifier) and two online BCI runs. Thus, each participant did 12 online BCI runs for each feedback condition.

In each session, a classifier was updated based on the data set from the BCI training run and it was used for the online runs in the same session. Such continuous updating of the classifier parameters reduces the amount of practice needed to achieve effective use of a BCI system [47,48]. The quality of the training classifier was validated with 5-fold cross validation right after the training runs; if training classification accuracy was less than 50% the participant redid the training, and if it was above 50% they went on to do the online runs. For both training and online BCI runs, EEG signals were monitored to make sure that all the EEG channels were properly connected and the signals were successfully recorded during the entire run.

During the classifier training run, the participants sat in front of a monitor and performed the motor imagery task according to a cue (i.e. MOVE or REST) displayed on the monitor. The cue was randomly assigned in 24 trials in each BCI training run (i.e. 12 trials for each cue condition), ensuring counterbalance. The sequence of the cue was as follows: 1) five seconds of a blank screen, 2) two seconds of a cross displayed on the screen, and 3) six seconds of the cue (either MOVE or REST) while the participant performed motor imagery about the task indicated by the cue (see Figure 3). For training before the visual feedback condition, the participant's arms rested on a table in front of them. When the cue indicated MOVE, the participants were instructed to imagine their arm moving from right to left until the monitor displayed the blank screen again. When the cue indicated REST, the participants were instructed to imagine no movement. For training before the kinaesthetic haptic feedback condition, the same sequence of the cue was used, but the participants placed their right hand over the end-effector of the haptic robot interface, and when the cue indicated MOVE, they were instructed to imagine their arm moving from right to left, and the haptic robot interface moved from right to left, regardless of their EEG signals.

Likewise, during the online run, the participants performed the motor imagery tasks according to the cue displayed on the monitor. The sequence for the online run was similar to the training run. However, instead of six seconds of the cue, the cue was displayed for 1.25 seconds and then there were eight seconds of feedback provided (see Figure 3). For the visual feedback condition, a bar indicator representing the confidence value was provided. For the kinaesthetic haptic feedback condition, the haptic interface continuously guided the participant's hand from right to left as long as the confidence value of the classification was above 0.6, and stopped guiding it when the confidence value dropped below 0.6.

To prevent movement artifacts, participants were asked to avoid strong blinking and head movements. In addition, they were asked not to push the haptic robot interface, and the force the participant put on it was measured to confirm that the participant was not physically pushing it (i.e. it was only moving by their motor imagery). Maximum interaction force detected from the interface was set to 4 N, chosen based on a pretest, to avoid active movements by participants. If more than 4 N of interaction force was detected from

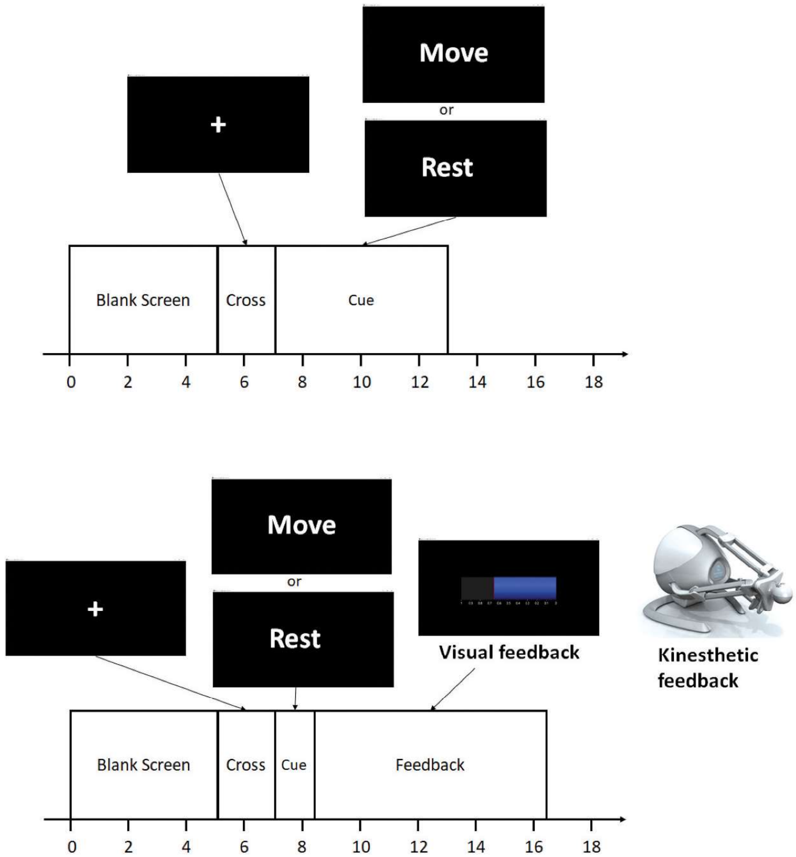

Figure 3. Timing diagram of a training BCI run (top) and an online BCI run (bottom).

the interface, it was assumed that the participant was performing an active movement rather than a passive movement and that EEG data were excluded from the analysis. Only 1.2 % of the total data needed to be excluded due to this.

The North American Space Agency Task Load Index (NASA-TLX) was used to examine participants' experience of workload with each feedback modality. The NASA-TLX is a commonly used method to evaluate subjective mental workload when using human technology interfaces [49]. It examines the workload in six different aspects: Mental Demand, Physical Demand, Temporal Demand, Own Performance, Effort, and Frustration Level [50]. Participants rated each aspect, from 0 (low) to 20 (high), on a printed form of the NASA-TLX after all six sessions with that condition were done. Related participant comments were recorded.

2.5. Measurements and analysis

EEG data during the cue part of the training run was used to train the classifier, and EEG data during the feedback part of the online run was used to evaluate the performance of the online classification. The data between the trials was excluded from measurements and analysis. Accuracy of the classifier was obtained by 5-fold cross validation in each training run (hereinafter referred to as 'training classification accuracy'), and online classification accuracy was calculated as the percentage of the number of correct classification predictions divided by the total number of classification predictions from each online run. Pearson's correlation coefficients between the training and online classification accuracies were also calculated for each feedback condition.

To determine if there was a statistically significant difference in online classification accuracy between feedback modalities and runs, the online classification accuracy was entered into a 10,000 bootstrapped two-way repeated measure analysis of variance (ANOVA) with the following factors: factor 1 was the online run (12 levels: 1 to 12) and factor 2 was the type of feedback (2 levels: visual feedback and kinaesthetic haptic feedback). Also, simple linear regression modeling was used to examine the linear trends of the BCI training over time. Since high variability of individual BCI performance is a well-known issue of many BCI applications [51], the results of individual performance were also plotted to examine individual differences.

Power spectrum density, which represents the distribution of the EEG power in the frequency domain, was calculated and plotted for each individual to examine how brain activity differed between the motor imagery task with visual feedback compared to kinaesthetic haptic feedback. Also, the short-time Fourier transform (STFT) spectrograms during the tasks with 3 s before to 7 s after the MOVE cue onset were obtained as the time-frequency analysis of the EEG power for each individual. Both plots were analyzed descriptively and categorized by types of spectral patterns. In addition, the spectral power differences from REST to MOVE for all the EEG channels during the motor imagery task were compared, as in other studies [13,18]. The frequency bands selected were: the low-alpha band (eight to 10 Hz), the high-alpha band (10 to 13 Hz), the low-beta band (13 to 16 Hz), and the high-beta band (16 to 26 Hz) [52].

3. Results: Study 1

3.1. BCI Classification accuracy

Figure 4 shows the training classification accuracy (estimated by the cross validation from the training runs) and the online classification accuracy for the visual and kinaesthetic haptic feedback for each participant. None of the adult participants without impairments needed to repeat any BCI classifier training runs since their training classification accuracy was above the minimum 50%. Eight out of 10 participants had an accuracy that was higher with the kinaesthetic haptic feedback, and one

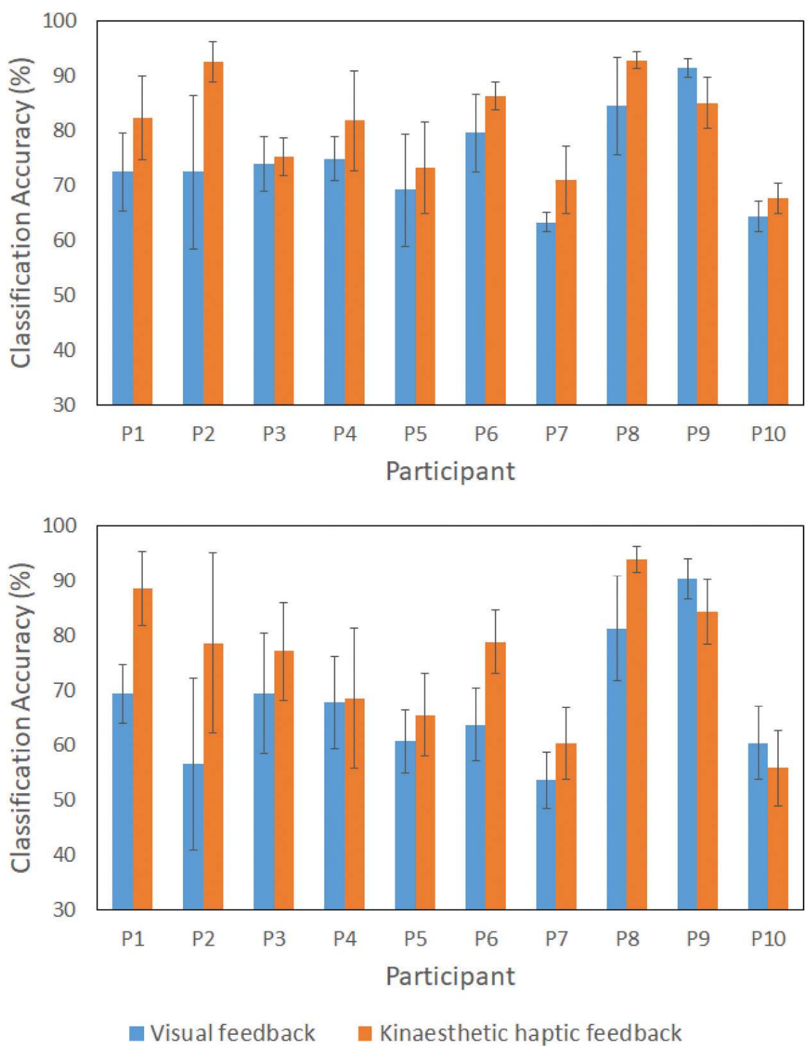

Figure 4. Training classification accuracy (top) and online classification accuracy (bottom) of the visual feedback and the kinaesthetic haptic feedback for all the participants. Error bars represent one standard deviation.

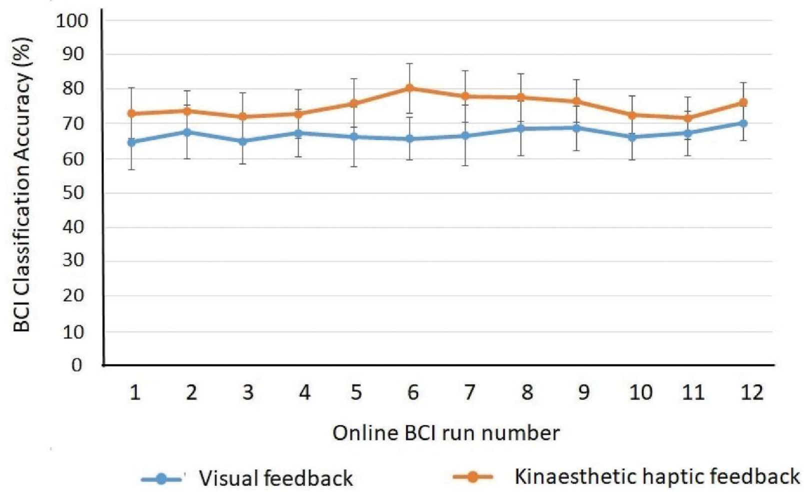

Figure 5. Average BCI classification accuracy across the 12 online BCI runs for adult participants without impairments. Error bars represent one standard deviation.

participant, P9, had an accuracy that was higher with the visual feedback, for both training and online BCI runs. One participant, P10 had higher accuracy with kinaesthetic haptic feedback in the training run but higher with the visual feedback in the online run. In the online classification accuracy, the error bars representing one standard deviation do not overlap between the two feedback conditions for P1, P6 and P8. The Pearson's correlation coefficients between the training and online classification accuracies were r = 0.82 for visual feedback and r = 0.93 for kinaesthetic haptic feedback.

Figure 5 shows the average online classification accuracy for all the participants on each BCI run for both feedback conditions. The participants completed the BCI training at an average accuracy of 67.28% (standard deviation 11.2) for visual feedback and 75.12% (standard deviation 12.3) for kinaesthetic haptic feedback. The bootstrapped two-way repeated measure ANOVA (factor 1 = runs, factor 2 = type of feedback, 10,000 repetitions) revealed that there was a statistically significant difference between the classification accuracy of the two feedback conditions, but the runs and the interaction of the two factors did not reach significance ($F[11, 99] = 0.72$, $p = 0.72$ for the runs, $F[1, 9] = 6.73$, $p = 0.03$ for the type of feedback, and $F[11, 99] = 0.60$, $p = 0.83$ for the interaction of the two factors). The regression line of the average online classification accuracy with respect to the run showed a small positive slope linear relationship for both feedback conditions (0.29 for the visual feedback and 0.11 for the kinaesthetic haptic feedback).

3.2. Spectral band power

Figure 6 shows the power spectrum density of the C3 EEG channel for the run with the median online classification accuracy of each participant. Channel C3 was selected because it was on the contralateral side to the hand used during the task and it is believed to be involved in brain activity related to motor imagery [13]. Figure 7 shows the STFT spectrograms of the C3 EEG channel for both feedback conditions before and after the MOVE cue onset. Suppression of EEG oscillation in the alpha frequency band after the cue onset (i.e. ERD), and increase of EEG oscillation in the beta frequency band after the cue onset (i.e. ERS), were indicated according to visual inspection. From the spectrograms, four participants show a clear brain response after the cue onset for the visual feedback (i.e. P3, P6, and P9 show ERD, and P4 and P8 show ERS), and seven participants show a clear response after the cue onset for the kinaesthetic haptic feedback (i.e. P3, P6, and P9 show ERD, and P1, P2, P4, and P8 show ERS). These brain patterns are also shown in the power spectrum density of Figures 6 that the participants demonstrate three types of responses: 1) P3, P6, and P9 show a clear ERD response; 2) P1, P2, P4, and P8 show a clear ERS response; and 3) P5, P7, and P10 show no clear response, with only a small difference between REST and MOVE in both feedback conditions.

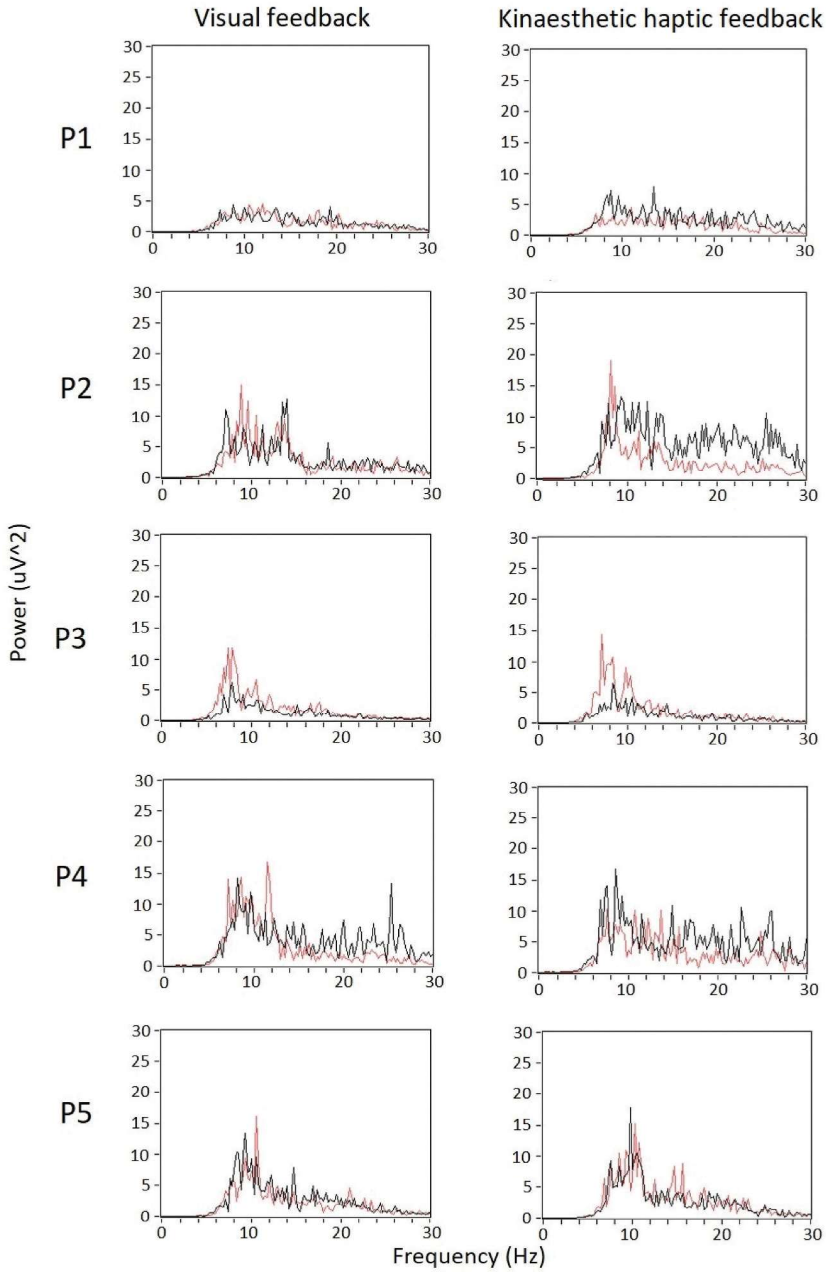

Figure 6. Power spectrum density of the EEG channel C3 during MOVE (black line) and REST (red line) for the two feedback conditions for the adults without impairments.

Figure 8 shows the spectral band power differences from REST to MOVE in the low-alpha, high-alpha, low-beta, and high-beta frequency bands. From the Figure, we can see that P3 and P6 have clear negative spectral band power differences in all the frequency bands in both feedback conditions, while the rest of participants show both positive and negative spectral band power differences depending on the frequency band and feedback conditions. The results also indicate that the error bars of the two feedback conditions do not overlap in at least one of the power bands in six out of 10 of the participants (i.e. P1, P2, P4, P6, P8, and P9). P1 and P8 have no overlap in three of the power bands and P6, has no overlap in two of the power bands.

3.3. NASA-TLX

Figure 9 shows the average participant scores of the six workload aspects in the visual and kinaesthetic feedback conditions. In all six workload aspects, the score of the workload with kinaesthetic haptic

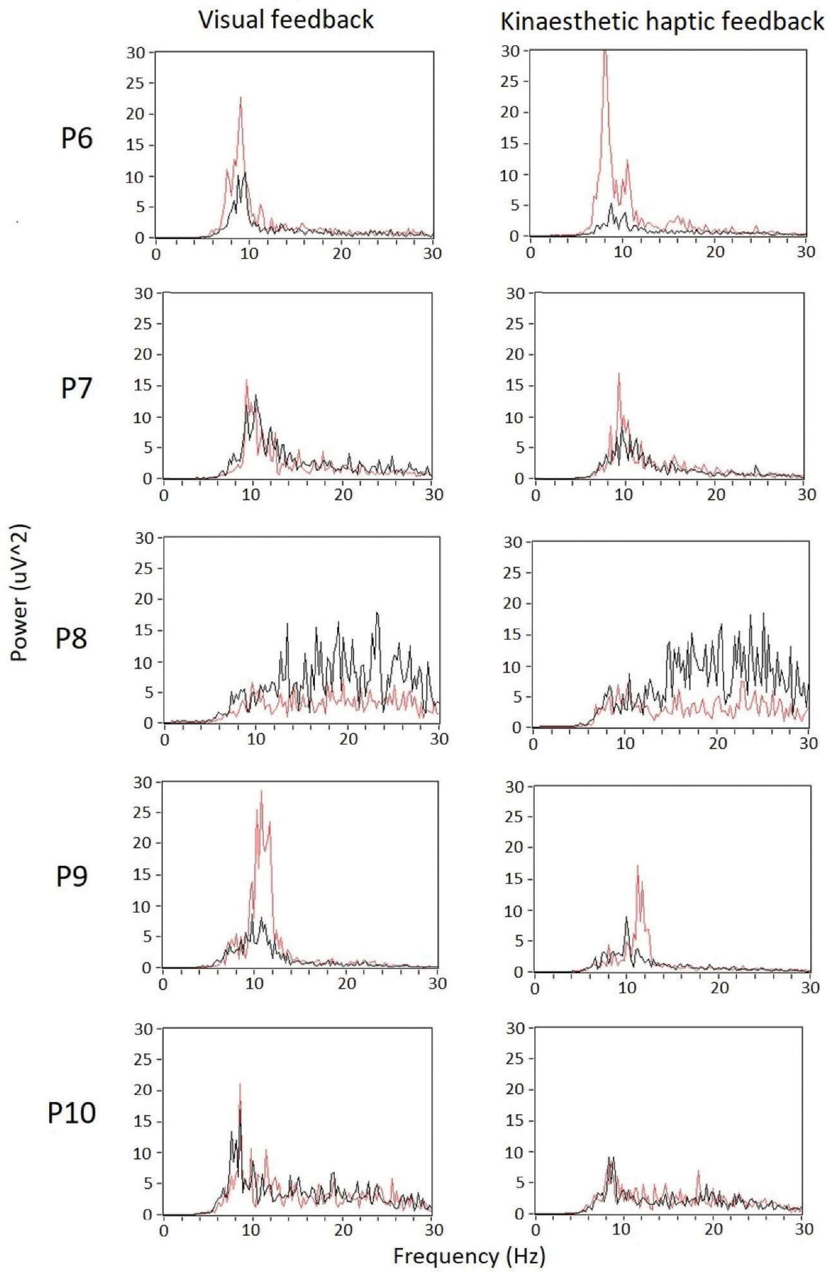

Figure 6. (Continued).

feedback was lower than with visual feedback. One participant commented that she preferred kinaesthetic haptic feedback because she could feel her arm moving from right to left, so she could easily focus on imagining that movement. Another participant said that the visual feedback was better because he could see in real time how calm he was becoming during the relaxation part because of the bar indicator on the display. Some participants commented that the visual feedback gave them more fatigue and involved more possibilities of distraction, while the kinaesthetic haptic feedback required less concentration during the task. However, another participant commented that the kinaesthetic haptic feedback was distracting during the REST phase when the EEG signal was incorrectly classified and the haptic robot interface moved.

Study 1 demonstrated that the kinaesthetic feedback did provide some classification accuracy improvements, but there were some issues that needed to be addressed before trials with children and/or individuals with impairments. First, it was noted that participants in Study 1 did not find the interface to be very engaging. Motor imagery-based

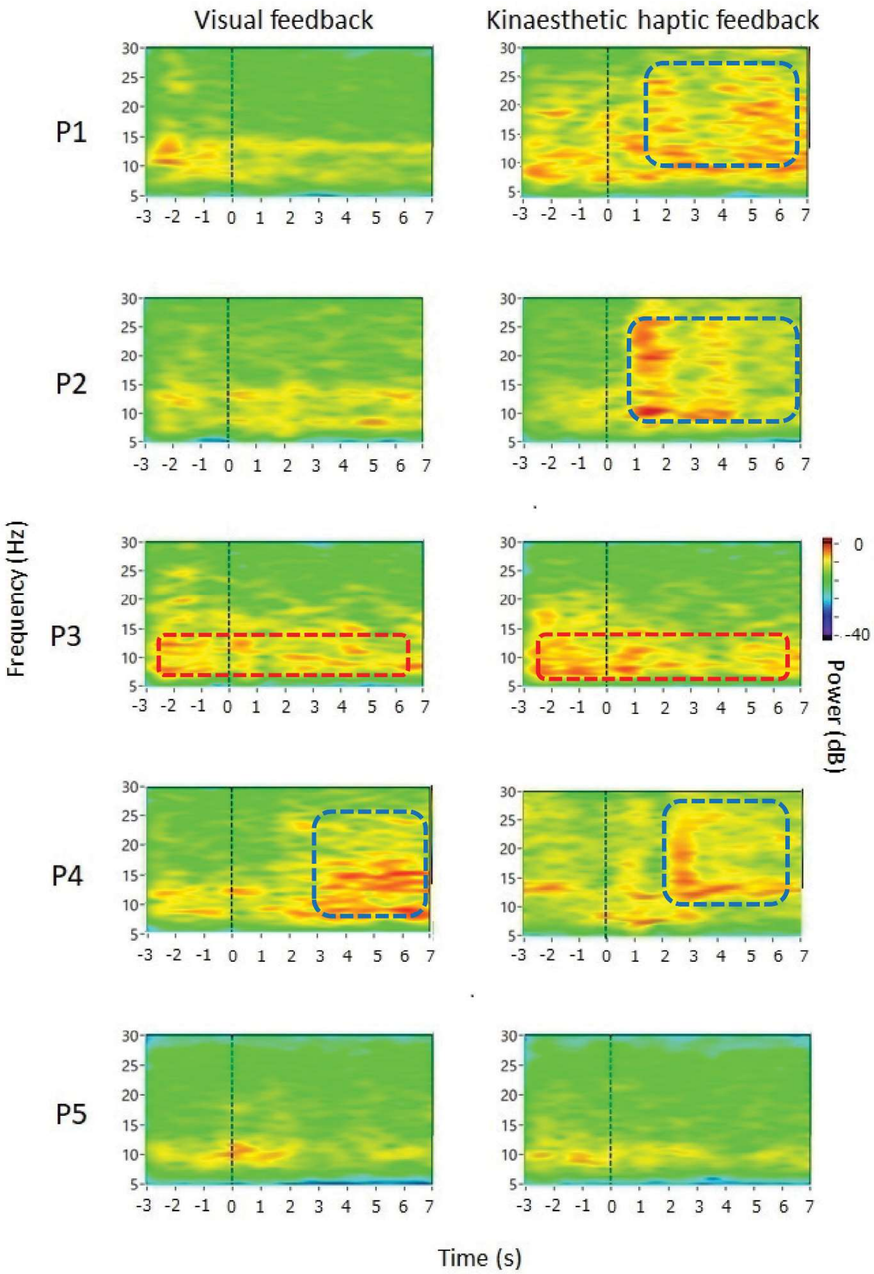

Figure 7. STFT spectrogram of the EEG channel C3 during the tasks with 3 s before to 7 s after the MOVE cue onsets for the two feedback conditions for the adults without impairments. Boxes with red dotted lines indicate ERD, and boxes with blue dotted lines indicate ERS. Vertical black dotted lines indicated the cue onsets.

BCI training protocol is generally said to be time-consuming and tedious [53], so we tried to make it more motivating and playful for Study 2. Second, since 12 runs did not improve BCI classification accuracy for the adults without impairments in Study 1, we reduced the number of runs and sessions to something that would not be too much burden on the participants, but enough to begin to explore the brain responses in this task. The ethical approval, experimental setup, procedures, and measures were the same as in Study 1, except for the following modifications.

4. Methods: Study 2

4.1. Study design

Exploratory case studies were performed to explore if the feedback may be beneficial for a child without impairments and an adult with physical impairments.

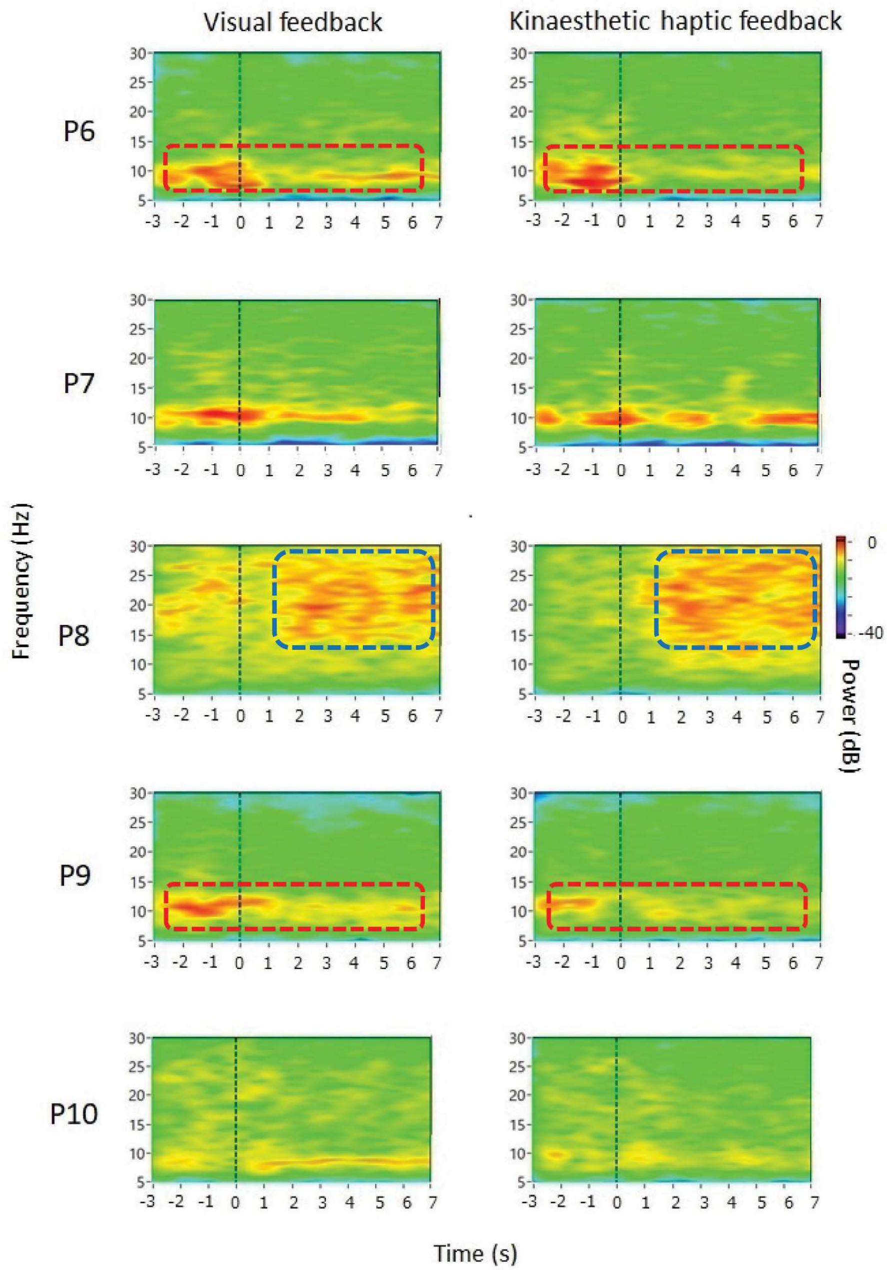

Figure 7. (Continued).

4.2. Participants

The system was tested by one 10 year, two month old child without impairments, C1, and a 48-year-old female with quadriplegic cerebral palsy who has mixed high and low muscle tone and involuntary movements, AD1. She has been classified as Level IV in the Gross Motor Function Classification System Expanded and Revised (GMFCS-E&R) [54], and Level III according to the Manual Ability Classification System (MACS) [55], meaning that she performs self-mobility by using a powered wheelchair and has difficulty handling objects.

4.3. Experimental setup

The BCI system was modified to a game-like application. Instead of visual feedback using the simple bar indicator in Study 1, a car and traffic light were displayed on the computer screen, and the car moved during the motor imagery task according to the confidence value of the LDA classifier (See Figures 10 and 11).

4.4. Procedures

A total of four online BCI runs for each modality were performed. There were two sessions on different days.

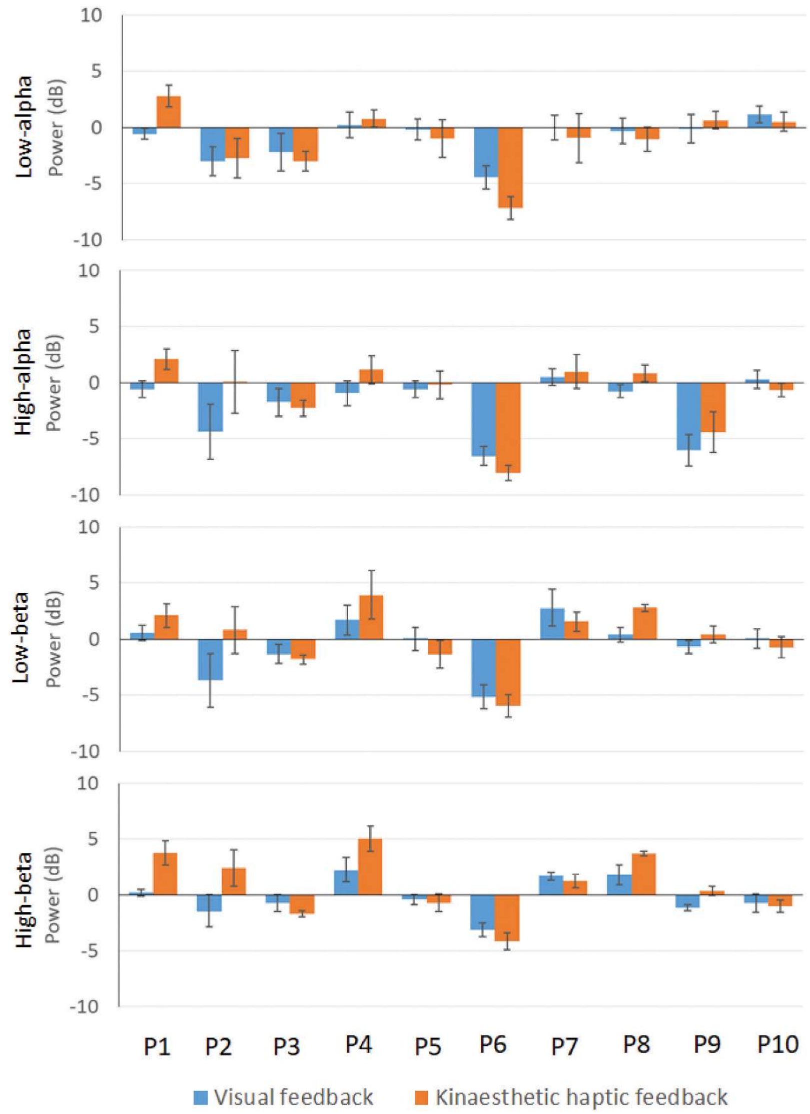

Figure 8. Spectral band power differences from REST to MOVE in the four different frequency bands of the visual and kinaesthetic haptic feedback for all of the adults without impairments. Error bars represent one standard deviation.

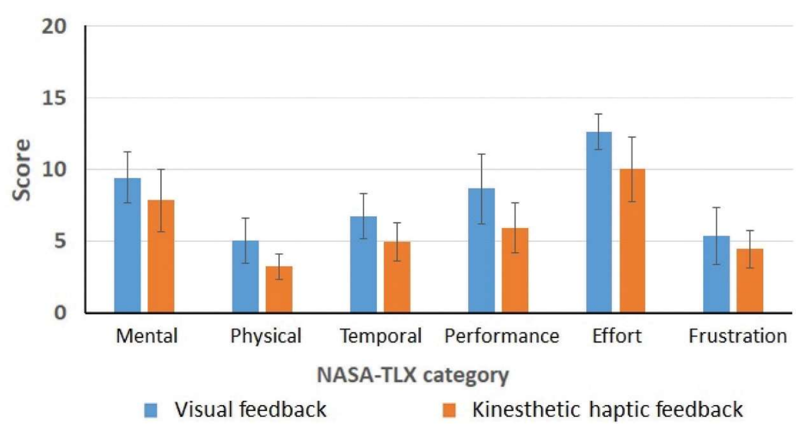

Figure 9. Average scores of each aspect of NASA-TLX for the adult participants without impairments. Error bars represent one standard deviation.

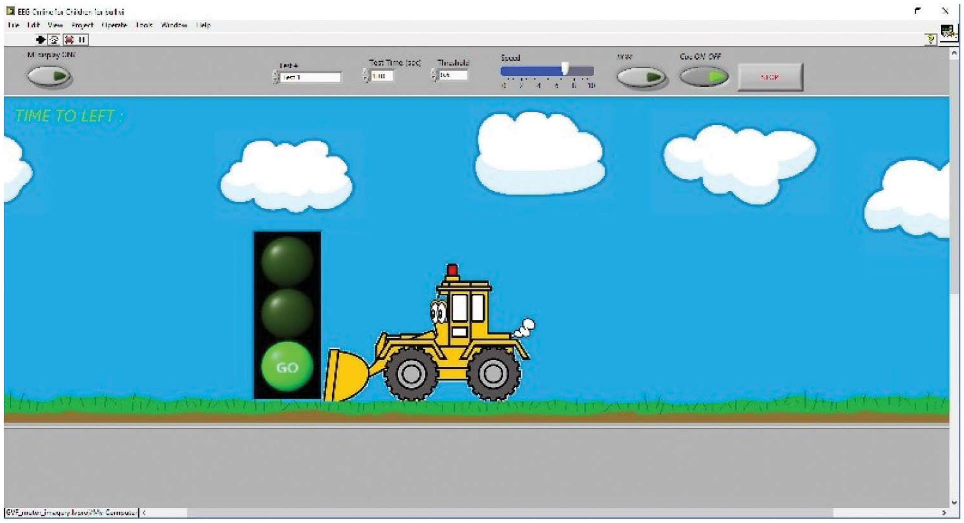

Figure 10. The graphical user interface of the experiment for children and adult with physical impairments.

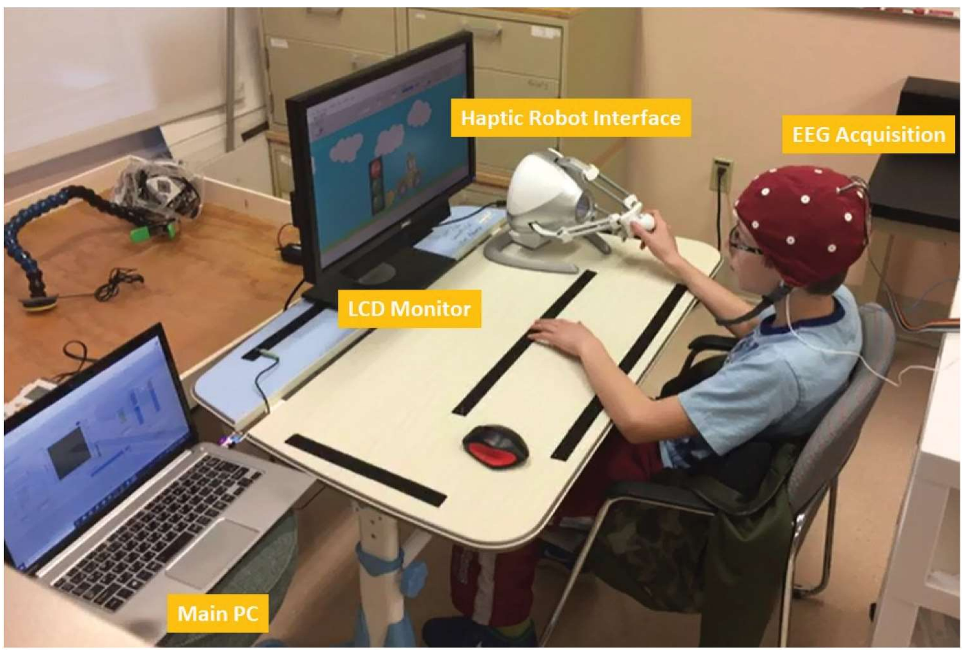

Figure 11. Picture of the BCI system for children and adult with physical impairments.

Each session lasted about one hour, including system setup, one BCI classifier training run and two online runs for each feedback condition. During the BCI classifier training, the participants sat in front of a monitor and performed the motor imagery task according to the traffic light displayed on the monitor. The task cues were green light for MOVE, yellow light for READY, and red light for REST. The cue was randomly repeated six times in each run. The sequence of the cue was as follows: 1) five seconds of all the lights off, 2) two seconds of the yellow light on, 3) six seconds of either the green light or the red light on. For the visual feedback condition, the participant's hands rested on the table during the task. When the green light was on, the car began to drive from the right to the left. During this period, the participants were asked to imagine their arm moving from right to left until all the lights turned off. When the red light was on, the car stayed still, and the

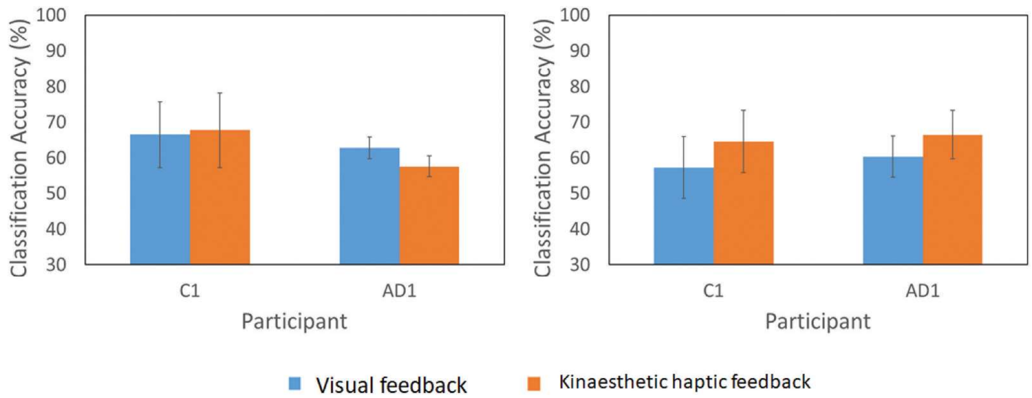

Figure 12. Training classification accuracy (left) and online classification accuracy (right) of the visual feedback and the kinaesthetic haptic feedback of both participants. Error bars represent one standard deviation.

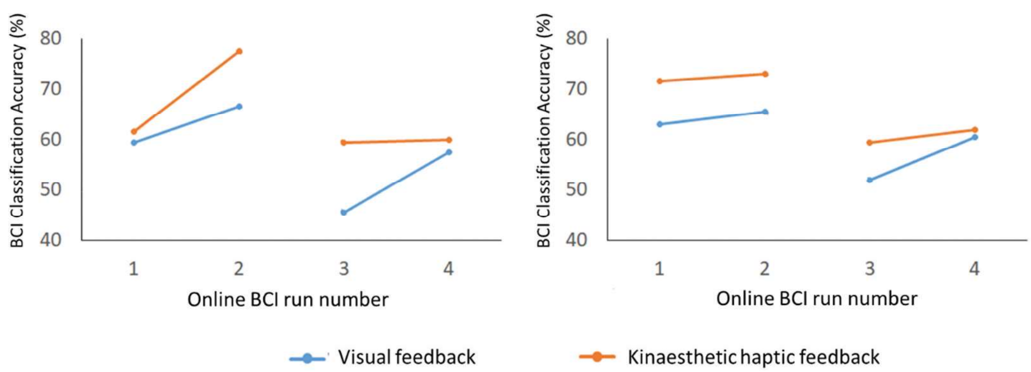

Figure 13. BCI classification accuracy across the 4 online BCI runs with each feedback modality for C1 (left) and AD1 (right). Only the lines of runs were connected from the same session.

participants were asked to imagine no movement. For the kinaesthetic haptic feedback condition, the participants put their hand over the end-effector of the haptic robot interface during the task. The task was the same as the visual feedback condition, however, the haptic robot interface passively moved the participant's hand simultaneously with the movement of the car. No active feedback based on the user's EEG signals was given during the training runs as in Study 1.

For the online runs, the participants moved the car with their motor imagery. The car only moved when the system detected the motor imagery with the same confidence levels used in Study 1, which were 0.6 for both visual and kinaesthetic feedback. Otherwise, the procedure was the same as Study 1.

4.5. Measurements and analysis

The dependent measures were the same as Study 1 (i.e. training and online classification accuracy, spectral band power, and NASA-TLX), however, the participant's performance was evaluated individually based on descriptive statistics due to the low sample size.

5. Results: Study 2

Figure 12 shows the average BCI classification accuracy of the training runs and online runs for the visual and kinaesthetic haptic feedback for the child participant without impairments, C1, and the adult with physical impairment, AD1. The child participant, C1, needed to repeat one BCI classifier training run due to the cross validation accuracy being 46.4% rather than the minimum 50%. It can be seen in Figure 13 that the online classification accuracies tended to decline slightly over the runs for both feedback conditions. For C1, the slope of the regression line decreased by −2.7 for the visual feedback and −2.25 for the kinaesthetic haptic feedback, and for AD1 the slope decreased by −2.1 for the visual feedback and −4.2 for the kinaesthetic haptic feedback.

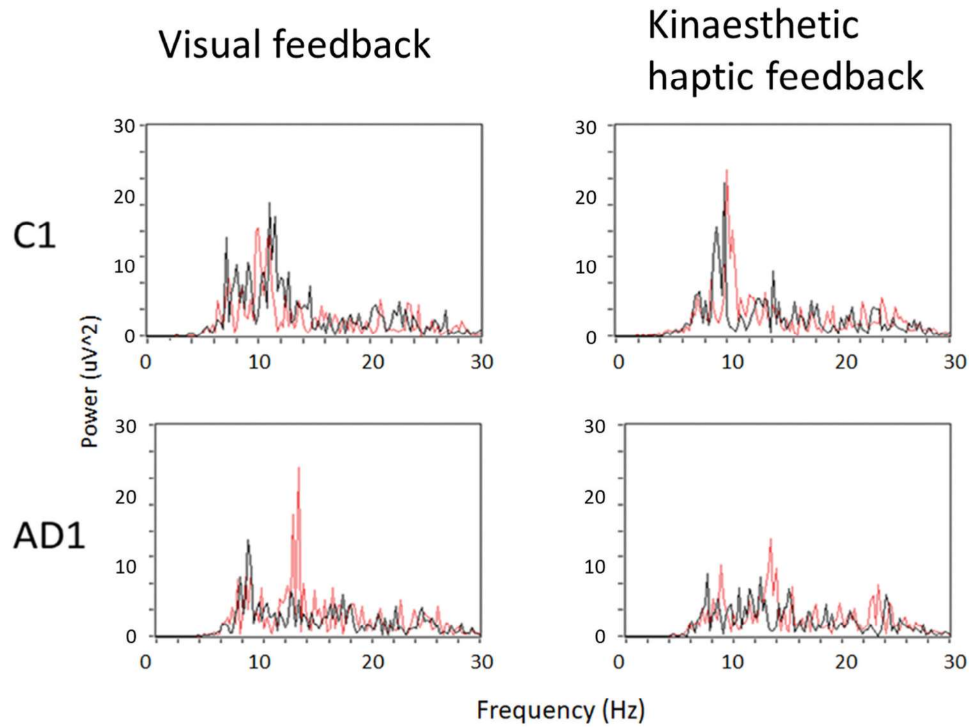

Figure 14. Power spectrum density of the EEG channel C3 during MOVE (black line) and REST (red line) for C1 and AD1.

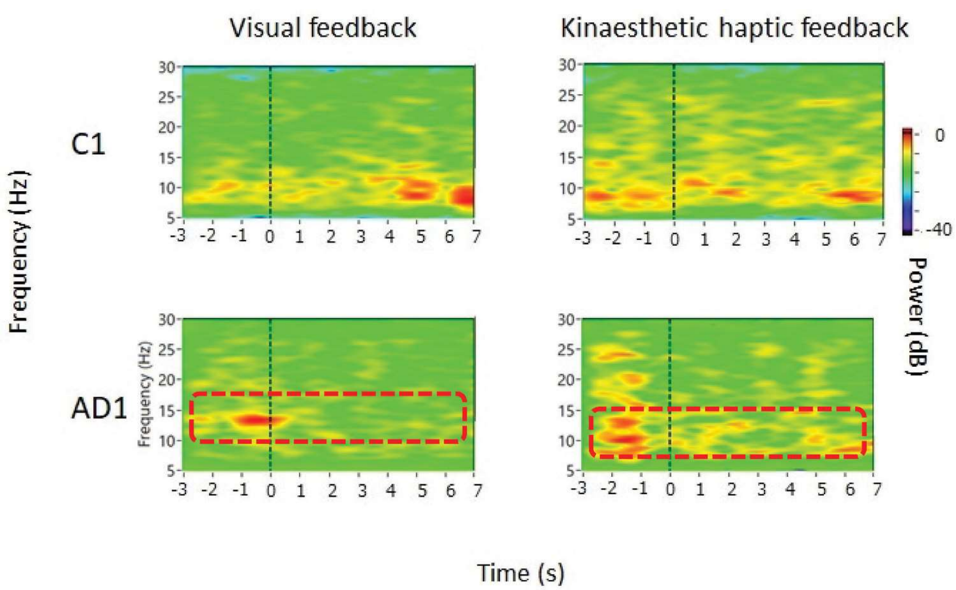

Figure 15. STFT spectrogram of the EEG channel C3 during the tasks with 3 s before to 7 s after the MOVE cue onsets for the two feedback conditions for C1 and AD1. Boxes with red dotted lines indicate ERD, and boxes with blue dotted lines indicate ERS. Vertical black dotted lines indicated the cue onsets.

Figure 14 shows the power spectrum density in channel C3 for the run with the median online classification accuracy for both participants, and Figure 15 shows the STFT spectrograms of C3 during both feedback conditions before and after the MOVE cue onset. A peak frequency around 10 Hz can be seen in both feedback conditions for the child participant, C1. The power spectrum density for the child shows the spectrum patterns during MOVE and REST were quite similar, and a clear ERD and ERS were not observed in the spectrograms. On the other hand, AD1 shows a clear peak frequency around 13.5 Hz, and the amplitude of the peak increased during REST and

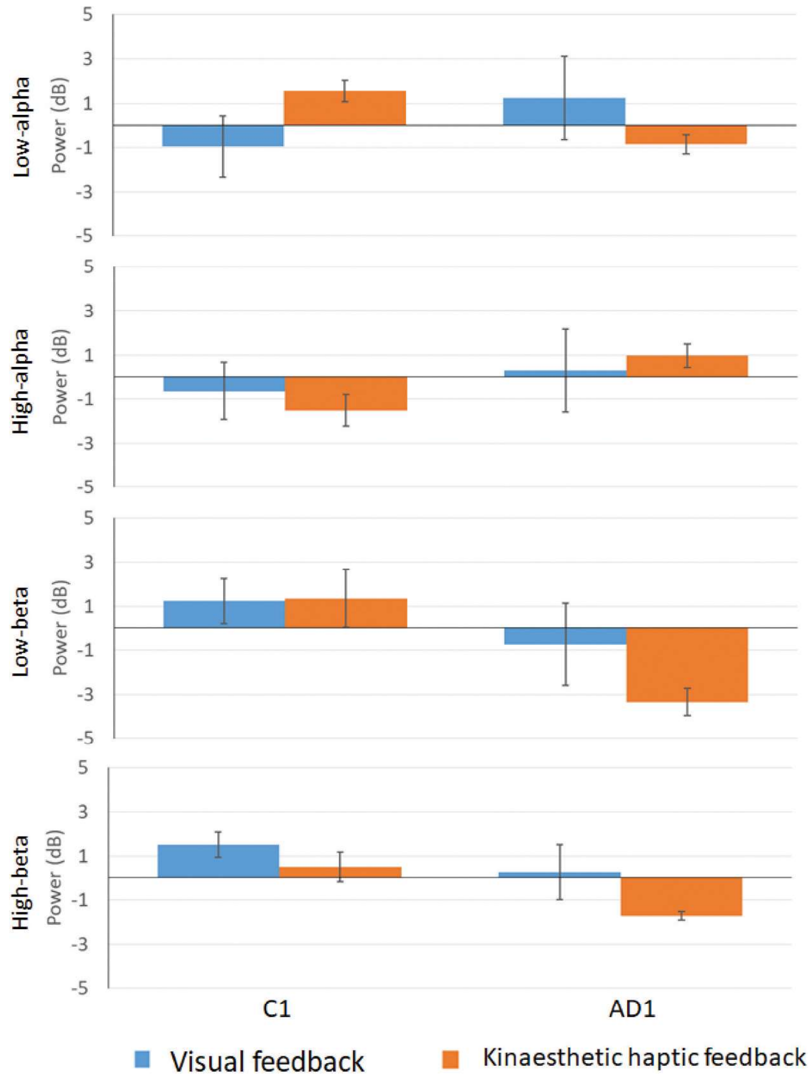

Figure 16. Spectral band power differences from REST to MOVE in the four different frequency bands of the visual and kinaesthetic haptic feedback for C1 and AD1.

decreased during MOVE in both conditions. This peak frequency also can be observed in the spectrogram of AD1; it appears before the MOVE cue and decreases after the cue onset.

The spectral band power differences from REST to MOVE caused by motor imagery in the four different frequency bands for C1 and AD1 are shown in Figure 16. For C1, the expected alpha band power decreases for MOVE appeared in the high-alpha frequency band, and the expected beta band increases appeared in the low and high-beta frequency bands, for both feedback conditions. However, the amplitude of the power differences between REST and MOVE in both visual and kinaesthetic was quite small. For AD1, a distinct power decrease was detected in the low beta band in both feedback conditions, and small positive or negative power differences were observed in the other frequency bands.

For C1 and AD1, the workload scores of the kinaesthetic haptic feedback were equal or lower than the scores for visual feedback (see Figure 17).

6. Discussion

6.1. BCI classification accuracy

The use of kinaesthetic haptic feedback during BCI training resulted in a statistically significant higher online classification accuracy than using visual feedback in Study 1 with adults without impairments. The sample size in this study was small, so no definitive statements can be made, but the study enabled some initial exploration into whether kinaesthetic feedback could provide

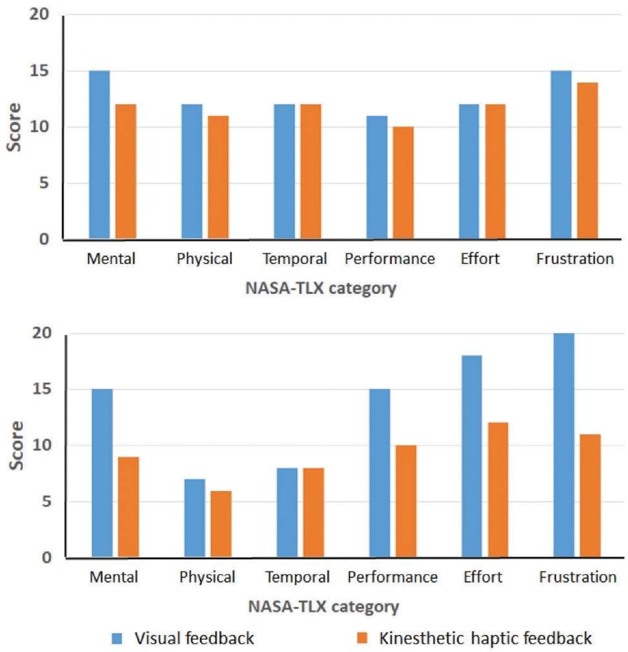

Figure 17. NASA-TLX score of each workload aspect for C1 (top) and AD1 (bottom).

some beneficial effect. BCI classification accuracy varied considerably between individuals. For seven out of ten participants, the online classification accuracy was higher with the haptic feedback, for one it was about the same, and for two participants the accuracy was higher with visual feedback in Study 1. The participants who had high accuracy using one feedback modality also had high accuracy using the other modality. The training classification accuracies were higher than the online classification accuracies in the visual feedback condition for all participants. However, the online classification accuracies were higher than the training accuracies in the haptic feedback condition for three participants (i.e. P1, P3, and P8). One potential reason is that there may not have been enough data for the cross validation. The training classification accuracy in this study was obtained based on the 5-fold cross validation, and the cross-validation may have produced biased performance estimates with small data size [56]. Another potential reason could be that the active kinaesthetic haptic feedback in the online runs enhanced the sensorimotor rhythms making it easier to detect and classify features which improved the classification accuracy over the training runs.

Individual variability is a common issue of many BCI applications [51], and a clinical implication could be that an examination of an individual's responsiveness to the haptic feedback should be done before investing time in training. The case studies in Study 2 involved a different number of sessions, BCI task, and analysis, so the results cannot be directly compared to Study 1. But, visual analysis of Figure 13 indicates that the child participant and the adult who had disabilities tended to have the same or higher BCI classification accuracy using the kinaesthetic haptic feedback than the visual feedback.

No statistically significant improvement in the online classification accuracy across the runs was found in either feedback condition over the 12 online runs for the adults without disabilities. A positive linear trend for the BCI classification accuracy was found for both feedback conditions, but the slope values were not large. The child without impairment and the adult with cerebral palsy actually showed a slight decrease in the BCI classification accuracy over the four runs. 57,state that BCI performance should improve through sets of BCI training. However, the duration of sessions and the number of the sessions required was not thoroughly discussed. Training given in previous BCI studies was from a few BCI runs in one day to more than 50 runs over several months [16,58]. It is possible that even 12 runs was not sufficient to show an improvement.

6.2. Spectral band power

The examination of the brain signals during motor imagery showed differences across participants, and some differences between feedback modalities. To accurately classify the motor imagery task, it is essential to have a clear difference in the brain patterns between MOVE and REST. The participants who exhibited clear ERD or ERS brain patterns tended to have better BCI classification accuracy than the participants who did not have a clear response (i.e. P3, P6, and P9 showed clear ERD, P1, P2, P4, and P8 showed clear ERS, and they had the higher classification accuracies in Figure 4).

In previous studies of motor imagery, suppression of alpha frequency band (i.e. ERD) and an increase of beta frequency band (i.e. ERS) after the movement onset are both observed in participants in a single task [59,60]. However, in this study, only one of the brain patterns, either ERD or ERS tended to be observed, depending on the participant (Figures 6 and 7). A possible reason for the variation in frequency band power across the participants is that the classifier used for this study was designed based on 1-second epochs, which could be too short to capture both ERD and ERS patterns. Likely, the classifier in this study classified the brain response based on either ERD or ERS, whichever was the stronger pattern generated by the participant. Epochs of a longer time frame could be a solution, however, longer a time frame would make system response slower and may not be practical in real-time BCI applications, such as robot control. Another solution could be use of two classifiers [i.e. ERD-based and ERS-based) in a single BCI system, as in 61.

In the comparison of the spectral band power differences from REST to MOVE in the four different frequency bands, the one standard deviation error bars between the two feedback conditions did not overlap in at least two of the power bands in three out of 10 participants in Study 1 (i.e. P1, P6, and P8]. These three participants also show that the online classification accuracy was higher with the kinaesthetic haptic feedback in Figure 4. The passive movement initiated by the kinaesthetic feedback through the haptics robot interface could have elicited sensorimotor rhythms similar to the brain activity associated with motor imagery. Thus, the premise in the study by 13,about the ERD/ERS response being induced by passive movement may have been beneficial in improving BCI classification accuracy in this study.

In Study 2, the child participant did not show much difference in power spectrum density and spectral band power differences between REST and MOVE in either feedback condition. According to a study by 23, the ERD response can be observed even in infants, and generally, the frequency of the ERD gradually increases until the age of about five. The EEG of the 10-year-old boy should be developed, but like some adult participants in Study 1, his power spectrum density did not show a clear ERD or ERS response. On the other hand, the adult with impairment showed a peak frequency of around 13.5 Hz in her power spectrum density and spectrogram in both conditions. Because the boundary of the frequency range between alpha and beta band was set to be 13 Hz, this peak frequency looked like the low-beta band in this study. As seen in Figure 14, the amplitude of her low-beta peak increased during REST and decreased during MOVE. Also, from the spectrogram in Figure 15, suppression of the 13.5 Hz band power was observed after the MOVE cue onset. From such a behavior, decreases in this peak amplitude should be considered an ERD response. Even though her ERD appeared at a slightly higher frequency than the participants in Study 1, the system was still able to classify her brain activity as REST or MOVE, with up to 66.5% accuracy. There was more potential to acquire distorted EEG signals from the adult with impairment because she often made reactive movements when she realized that the system misclassified her movement intention during the task. These reactive movements likely caused muscular artifact in her EEG signals. However, by using the temporal and spatial filters to minimize the artifact and noise, this BCI system could still potentially have differentiated between the two conditions of the motor imagery task (i.e. MOVE and REST).

6.3. Mental workload

Lastly, regarding the user's response of workload, all the participants without impairments reported less workload for the motor imagery task with kinaesthetic haptic feedback than with visual feedback. The kinaesthetic haptic feedback had advantages like the reinforcing effect of the actual movement of their arm during motor imagery, and it had disadvantages like distraction when signals were misclassified. However, the visual feedback tended to be quite fatiguing for the participants. The scores of the child and the individual with impairment also indicate higher workload for the visual feedback than the kinaesthetic haptic feedback. The range of the workload scores are wider for the child and the individual with impairment than those of the adult participants without impairments (i.e. ranging from five to 20 compared to five to 12). The higher scores could be because of having less tolerance to wearing the uncomfortable EEG cap, concentrating during the motor imagery task, or keeping the body posture still during the task to avoid muscular artifact. The one-hour session may have been too long for them, and indeed, the individual with impairment reported fatigue with both feedback modalities above. BCI tasks require focused attention, and the long BCI sessions often make participants feel tired [53]. Lack of concentration and focus during the BCI trials can negatively affect a user's BCI performance. Therefore, a shorter session time, for example, no more than 30 minutes, would be better for BCI sessions with children and adults with disabilities.

6.4. Limitations

This study has limitations, which should be acknowledged. First, due to the small sample size (i.e. ten adults, and two case studies), the findings cannot be generalized and can serve only as preliminary data guiding further research. Second, the strong linear relationship between the training and online accuracy for both feedback conditions for the participants without disabilities (i.e. Pearson's correlation of $r = 0.82$ for visual feedback, and $r = 0.93$ for kinaesthetic haptic feedback) means that the online classification accuracy heavily depended on the quality of the training run. Thus, the online runs were limited in the accuracy they could reach. Third, in order to proceed to the online runs the threshold for training classification accuracy was the theoretical chance level of 50%, which is not enough to say the accuracy was well above random chance. However, since the objective of this study was to evaluate improvement of BCI classification accuracy over time, we avoided setting a higher threshold, which would have required more training runs and resulted in an unbalanced number of runs between participants. In this study, only the child participant, C1, failed one training run due to classification accuracy being less than the 50% threshold, and for most participants training classification accuracy was much higher (e.g. 74.5% (standard deviation 10.8) for visual feedback and 80.8% (standard deviation 9.9) for haptic feedback for participants without disabilities). Fourth, the participants in Study 2 were asked to drive a car displayed on the screen with their motor imagery, whereas the participants in Study 1 controlled the value of a bar indicator. Thus, the results of the two studies are not comparable in the strictest sense. Fifth, because of the nature of the game-like graphical user interface, the participants had the kinaesthetic haptic feedback in addition to the visual feedback (i.e. the moving car) during the task in Study 2, whereas the participants in Study 1 only had the kinaesthetic haptic feedback. The multimodal feedback may have resulted in higher BCI classification accuracy than the single mode feedback [32]. However, testing of the BCI system with haptic feedback by a child and an individual with impairments was beneficial to begin to explore the possibility of doing robot movement based on motor imagery signal. Next steps could include moving a physical car in the play environment for BCI training, rather than on a computer screen.

7. Conclusions

In this study, we explored a method for users to experience kinesthetic haptic feedback that passively moved their arm according to detected movement intention. This will be valuable in next steps of our study where users will feel the feedback about their motor imagery and be able to operate a robot without needing visual feedback.

BCI training using only kinaesthetic haptic feedback was compared with the traditional visual feedback displayed on a screen. The classification accuracy with kinaesthetic haptic feedback was significantly higher than the accuracy with the visual feedback in a study with ten adults. The accuracy was as good or higher for a child without impairments and an individual with physical impairments in case studies using a different interface and fewer runs. In order to be more appealing for children, the BCI interface was modified to a game-like activity in order to make the BCI task sustain their attention.

Participants may have perceived the sensory input that their own arm was moving which may have elicited the brain activity associated with motor imagery to improve classification accuracy. There is need for further research to explore using kinaesthetic haptic feedback with longer sessions and larger sample sizes, and to trial the system with children and adults with physical impairments.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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