Development and Testing of an Eye Gaze and Brain-Computer Interface with Haptic Feedback for Robot Control for Play by Children with Severe Physical Disabilities

by

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Abstract

BACKGROUND: The process through which children learn about the world and develop perceptual, cognitive and social skills relies heavily on spatial and object exploration; specifically, manipulation of toys and tools in the environment. However, some children with motor impairment have difficulties with object manipulation due to issues with selective motor control that affects reaching or grasping. Robots controlled through simple human interfaces (e.g., joysticks and switches) can be a bridging tool for children with disabilities to access play and related development opportunities because robots can perform reaching, grasping, and manipulation functions to compensate for the children's motor difficulties. These interfaces, however, generally still require a certain degree of physical ability to access and operate. Human-robot interfaces utilizing usable biological signals could be a potential solution to enable environmental exploration and object manipulation via a robot for people with motor impairments.

OBJECTIVE: The main objective of this thesis was to develop a human-robot interface which integrated low-cost eye tracker and brain-computer interfaces (BCI) to directly control a robot. The systems were adapted in order to interact in a physical play environment, i.e., without the need for a computer display. Alternatives to visual feedback were examined, such as auditory and haptic feedback, for their effectiveness in improving task performance.

METHODS: This dissertation work was divided into four phases involving experiments with adults and children with and without disabilities: 1) An eye gaze interface that mapped gaze direction into the physical environment was developed using homographic mapping. Participants used the system with different feedback conditions (i.e., visual, no-feedback, auditory, and vibrotactile haptic feedback) to select targets on a computer display and in the physical environment. 2) The eye gaze interface was then used in a physical task to sort cards using a teleoperated robot. First, the participant's desired target was determined using the eye gaze system. Then, a Forbidden Region Virtual Fixture (FRVF) was created towards the selected target to help the participant move the robot end effector towards it. The effects of no-feedback, auditory and vibrotactile haptic feedback for gaze fixations were examined. 3) Open BCI was used to implement a BCI based on event related desynchronization/synchronization (ERD/ERS). A motor imagery task was performed with feedback according to the detected movement intention, and the effectiveness of two feedback conditions was examined, the classic Graz training using visual feedback and kinesthetic haptic feedback using passive movement of the participant's hand. 4) The eye gaze interface and BCI were combined and tested in a physical play task with a mobile robot. Vibrotactile haptic feedback was given for feedback about gaze fixation and kinesthetic haptic feedback was given as feedback for motor imagery. The performance at selecting targets and moving towards them with and without the feedback was compared.

RESULTS: 1) Gaze interaction was performed significantly faster during feedback conditions compared to no-feedback ($p=0.019$). However, no significant difference in performance between the feedback modalities (i.e., visual feedback, no-feedback, auditory feedback, and vibrotactile feedback) were found. 2) Feedback for the gaze fixation and guidance of the FRVF did not improve the performance of the robot control task for the adults without impairments, however, it did improve the speed and accuracy of the task for the child and adult with impairments. 3) The BCI task with the kinesthetic haptic feedback was significantly more accurate than the task with visual feedback only ($p=0.01$). No significant improvement was observed over 12 BCI runs in both feedback conditions, however, the participants reported that the task with the kinesthetic haptic

feedback had a lower workload compared with the visual feedback only. 4) Using the mobile robot control task using the integrated eye gaze and BCI human-robot interface, all the adults without impairments and the adult with cerebral palsy performed faster during the no-feedback condition, and two of them showed significance ($p=0.01$ for the two adults without impairments). All the participants reported that task with the haptic feedback required less task workload.

CONCLUSION: Feasibility of the eye gaze interface and BCI for the integrated human-robot interface were confirmed throughout this research series. Adding feedback to the human-robot interface could improve the performance of the robot operation and would enable people with physical impairments to access play and subsequent learning opportunities.

Preface

This thesis is an original work by Isao Sakamaki. The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Health Research Ethics Board: “Biological Signals and Haptics-based Robot Control for Play by People with Severe Physical Disabilities”, Pro00071723, Sept 25, 2018.

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

The process by which children develop motor, perceptual, and cognitive skills relies significantly on their tactile experiences within the physical world and the way in which they explore objects (Gibson, 1988). Cognitive development spans elements such as thinking, learning, resolving, feeling, and knowing the environment, and the development of cognitive abilities can be facilitated by motor and perceptual experiences in day-to-day life (Bjorklund, 2005). For children who have severe physical impairments, one of the biggest concerns for cognitive development is the lack of opportunities for meaningful manipulation tasks, often in the context of play activities (Taylor, Imms, & Dodd, 2010).

Play is an enjoyable and natural way in which children interact with their social and physical environment in order to discover the world by testing different objects and experiences, and it also stimulates creativity, learning, mastery, self-expression, and adaption (Ferland, 2003). Children who have physical disabilities may find it difficult to participate in certain play activities as a result of impairments they may have, such as limitations in movement, grasping, and reaching for objects. Furthermore, children who have some form of physical impairment tend to watch others play as opposed to participating themselves because their playmates more effectively or frequently handle play activities on behalf of the child with physical impairment (Blanche, 2008). This can impede their development across multiple areas such as motor, social, linguistic, and cognitive skills (Harkness & Bundy, 2001).

Children can use robots to access play activities, controlled through a human-robot interface. Robots such as Lego robots (Ríos-Rincón, Adams, Magill-Evans, & Cook, 2016) and Play-ROB (Gernot Kronreif, Barbara Prazak, Martin Kornfeld, Andreas Hochgatterer, & Martin Furst, 2007) have enabled children with cognitive and physical impairments to manipulate objects for play. The human-robot interfaces for these robots were switches (Ríos-Rincón et al., 2016) and joysticks (Gernot Kronreif et al., 2007).

Simple button switches are common human-robot interfaces. They return a binary signal of "on" or "off" depending on if the switch is pressed or not. Switches can be placed in different anatomical locations to facilitate ease of access that may differ between individuals. Each switch controls one dimension of movement of the robot (e.g., forward or turn).

Joysticks are another common human-robot interface. Most joysticks operate using continuous signals, for example, the farther the joystick moves away from the starting point, the faster the robot goes. Also, they can control multiple dimensions of movement, (i.e., moving forward makes the robot move forward, and moving it left can make the robot go left). Research has shown that such human-robot interfaces can be successfully used with assistive robots, with joysticks being most intuitive (Harwin, Ginige, & Jackson, 1988; Gernot Kronreif et al., 2007; Rios, 2014). However, these interfaces require a certain degree of physical ability to access and to operate. If users have no voluntary and repeatable muscle control, which makes it difficult to initiate accurate physical movements, it would be impossible for them to operate those interfaces. There are interfaces that do not require the ability to control body movement, such as those that use eye gaze data or brain signals, and in recent years, the cost of these interfaces has become feasible for use in hospitals or homes (Gibaldi, Vanegas, Bex, & Maiello, 2017; Martinez-Leon, Cano-Izquierdo, & Ibarrola, 2016).

The ability to control eye movement is often retained when people lose physical bodily function (Rytterström, Borgestig, & Hemmingsson, 2016). Eye trackers are used to detect the user's eye movement and determine the location where they are focusing. It is often used as an access pathway for people with physical impairments to control a computer or an augmentative and alternative communication device (Biswas & Langdon, 2011). Because this is a pointing operation with eye movement, Fitts' law can be applied (Vertegaal, 2008). Fitts' law is a well-known model for evaluating pointing tasks in human- computer interactions. It says that the amount of time required for a person to move a pointer to a target area is a function of the distance to the target divided by the size of the target (Santos, Santos, Jorge, & Abrantes, 2014). Thus, the smaller the target's size, the longer it takes, implying a tradeoff between time of movement and size of target. This tradeoff was examined in this study by testing different target sizes of the gaze interactions.

In addition, robot control using eye gaze has been an increasingly studied topic. For example, Nguyen and Jo (2012) proposed an eye gaze-controlled powered wheelchair, maneuvered by selecting commands on a mounted display for navigation. In Encarnação et al. (2017), children controlled a mobile robot by selecting robot commands on a computer display. However, with these systems, participants had to look back and forth between the display and the environment, which requires changing the focus from one place to another. The participants could have worn a head-mounted display to circumvent this study limitation, but some people do not tolerate wearing such displays (Koulieris, Bui, Banks, & Drettakis, 2017).

Brain-controlled access pathways, often referred to as a brain-computer interfaces (BCI), can detect brain activity associated with real or imagined movement. Sensory processing of motor behaviour shows a change of the brain signals in the alpha frequency band (8 to 13 Hz), named Event–Related Desynchronization (ERD), and in the beta frequency band (13 to 26 Hz), named Event-Related Synchronization (ERS) (Pfurtscheller & Neuper, 2010). Thus, BCI detect brain activities associated with a user's movement intention and that information can be used to control a device. For example, a study of Marquez-Chin, Marquis, and Popovic (2016) demonstrated the use of BCI-based functional electrical stimulation therapy to initiate upper limb movement of people with physical impairments. The functional electrical stimulation was controlled based on the user's movement intention detected from their brain signals.

Combining a stationary eye tracker and a BCI have potential as an intuitive interface for robot control. The stationary eye tracker could be placed in front of the play environment and enable a user to directly select a desired spatial target or destination for the robot. The BCI could allow users to control a robot to move or stop using their movement intention, like a binary switch. Frisoli et al. (2012), used a head-mounted eye tracker and a g.tec BCI system (Guger Technologies OEG, Graz, Austria) to assist the movement of the upper limb in reaching exercises for neurorehabilitation. Participants with and without physical impairments were able to select a target location with eye gaze, and an exoskeleton facilitated the users' arm movement towards the location based on their motor imagery.

In order to perform reliable control of a robot in a physical play environment with a stationary eye tracker and BCI in functional robot tasks, certain issues need to be addressed. With a stationary eye tracker, users generally have biofeedback to control a visual pointer on a computer screen (hereafter "on-screen"). Biofeedback is a technique that teaches self-control of physiological functions by measuring and providing feedback information about those functions (Sigrist, Rauter, Riener, & Wolf, 2013). Having feedback about where the eye tracker is interpreting the gaze is crucial for successful gaze interaction (Majaranta, MacKenzie, Aula, & Räihä, 2006). However, for an application that does not involve a display ("off-screen" hereafter) such as selecting a target or destination for the robot in the physical play environment, visual feedback is difficult to provide. Alternatives to visual feedback are needed.

Auditory and haptic feedback have also been used as biofeedback strategies in eye gaze interactions. Haptic feedback can be divided into two types: vibrotactile haptic feedback is related to cutaneous receptors situated in the skin, and kinesthetic haptic feedback is related to receptors located in the muscles, joints and tendons of our body (Sigrist et al., 2013). A meta-analysis of 43 studies by Burke et al. (2006) found that the presentation of auditory and vibrotactile haptic feedback significantly enhanced the performance of selecting letters/words by eye gaze on the computer screen.

Likewise, BCI performance can be enhanced by biofeedback. Reliable classification of brain activity into "movement" or "no movement/rest" signals is crucial but classification may vary depending on the person (McFarland & Wolpaw, 2011). BCI training generally reinforces BCI control by visual presentation of feedback about motor imagery performance displayed on-screen. Different types of feedback modalities have been investigated. For example, Gomez-Rodriguez et al. (2010) examined the feasibility of kinesthetic representation of feedback in robot-assisted physical therapy for stroke rehabilitation. The results revealed that passive movements initiated by kinesthetic haptic feedback using a robot in a BCI training protocol enhanced EEG patterns similar to those observed during motor imagery. The study of Frisoli et al. (2012) reported that a higher BCI classification accuracy was achieved when kinesthetic motion guidance was provided by the exoskeleton to the users during reaching exercises.

Sensory information from perception and actions of our body are tightly coupled together and processed within our cognitive system (Gibson, 1988). Perception is an input from the environment, and action is an output from our body. This close link is called perception and action coupling. For example, accurate reaching movement for an object is guided by perceptual information specifying the relation between our body and the environment. In addition, our body is able to integrate multiple sensory inputs coming from different perception modalities in an efficient way, using this information to select and control its adaptive behavior in many situations in our daily activities (Lalanne & Lorenceau, 2004), This ability, called cross-modal integration, can be seen in hand-eye coordination. Hand-eye coordination involves many different sensory inputs processed simultaneously in order to perform an optimal motion of reaching and grasping an object, for instance. At the cortical level, visual and spatial information is processed in the occipital area, and motor action and sensing of haptic information is processed in the region of the central sulcus where the boundary between frontal and parietal lobes is, however, our cognitive system can handle the integration of multiple sensory information for bodily actions. In the case of hand-eye coordination, it requires not only visual perception, but also sensory information from arm and finger for the object to be reached and grasped. In this study, examining sensory information in addition to visual perception in the eye gaze interface, or haptic biofeedback instead of the conventional visual information in the BCI system, could be important to explore and understand the human-robot interfaces.

For eye gaze and BCI to be used for controlling a robot in a physical play environment, alternatives to a visual display are needed so users do not have to switch their visual attention between the display and the play environment. Adding auditory and vibrotactile feedback are a promising modality for eye gaze, and replacing kinesthetic feedback is a promising modality for robot control with the BCI. A combination of an eye tracker and BCI with alternatives to visual feedback could make it possible to intuitively control a robot in a physical play environment. Moreover, the use of low-cost interfaces could make the proposed system more affordable and accessible to more people who have difficulty accessing play.

1.1 Objectives and Research Questions

The final goal of this thesis was to develop a new human-robot interface that integrates eye gaze and BCI to allow users to directly control a robot in the physical environment, and to test the integrated human-robot interface in functional robot tasks. In addition, biofeedback modalities such as visual, auditory, and haptic feedback were added to the human-robot interfaces, and effectiveness of the different biofeedback modalities was examined.

This dissertation consists of four papers, presented in Chapters 3 through 6, to address the aforementioned research goals. In Chapter 3, development of an eye tracking system is described. The system was developed to map eye gaze direction between the coordinate frame of a stationary eye tracker and the objects in a play task environment. The effects of different feedback for gaze interaction in on-screen and off-screen conditions were examined. In Chapter 4, the eye gaze system was implemented in a functional robot task using a teleoperational robot platform based on a previous study. For off-screen robot control in the physical environment, feedback for BCI can be provided first, so they user can learn to generate sensory motor rhythms, and secondly, to aid in controlling the robot in a functional task. The former situation was examined and is described in Chapter 5, and the later situation is described in Chapter 6, where both eye gaze and BCI control were integrated to control a robot. The following research questions were addressed in the chapters.

1. How do speed and success of gaze interaction differ between on-screen and off-screen conditions?
2. Which feedback modalities and target size make the gaze-based target selection faster and more successful?
3. What is the feedback preference of the participants in both on- and off-screen gaze interactions?

Chapter 4 regarding the eye gaze system in a functional robot task:

1. Can auditory feedback or vibrotactile haptic feedback about gaze fixation location make target selection in a sorting task faster and more intuitive than without it?
2. Can haptic guidance pathways, determined by the gaze-based target selection, improve movement efficiency and ease of the robot operation compared to without it?

For Chapter 5 regarding BCI training:

1. Which feedback modality (visual or kinesthetic haptic) results in better BCI classification accuracy?
2. Can repeated runs of the BCI training with the feedback improve BCI classification accuracy over time?

3. How does brain activity differ in a motor imagery task with visual feedback versus haptic feedback?
4. Which feedback modality leads to a lower workload for the participants?

For Chapter 6, using the eye gaze and BCI system in a functional robot task:

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

1.2 List of Papers and Contributions

Chapter 3: Effectiveness of Different Biofeedback Modalities for Improving On-screen and Off-screen Eye Gaze Interaction.

In this study, by using a homogeneous transformation technique, eye gaze data were mapped between the gaze direction detected by a stationary eye tracker and the objects in the physical environment. The eye gaze system was tested with different feedback conditions (i.e., visual feedback, no-feedback, auditory feedback, and vibrotactile feedback) in a gaze interaction task in on-screen and off-screen conditions. For ten adult participants without impairments, their tasks with feedback modalities were accomplished statistically faster and more accurately than tasks performed without feedback in both screen conditions. The task in the off-screen condition was consistently slower than the task in on-screen condition. Three children without impairments, and two adults and one child with cerebral palsy also tried the system, and based on visual inspection, their performance on the tasks without feedback were slower than tasks with feedback modalities. Providing feedback appeared to help them to improve the speed of the gaze interaction task. There was no statistically significant difference in performance between the feedback modalities in the gaze interaction tasks, but participants had personal preferences, with the vibrotactile haptic feedback being the most commonly preferred. Vibrotactile haptic feedback was implemented in the integrated system of Chapter 6.

Chapter 4: Implementation of Eye Gaze with Biofeedback in a Human-Robot Interface

In a previous study, haptic feedback was used for guidance to help users move a robot to target locations in a card sorting task (Sakamaki, Adams, Medina, et al., 2017). The guidance was created by software-generated forces at the user interface that generated a clear pathway from a pick-up location to a drop-off location, and prevented movements elsewhere. The position of the guidance was determined by computer vision, so the system never allowed the users to make mistakes. In the study of this chapter, the haptic guidance pathways were generated based on eye gaze so users could indicate their intended target by gaze, even towards mistaken targets, so the system could be used in testing situations. The system was tested with ten adults without impairments, two children without impairments, and one adult with cerebral palsy. The users received several feedback modalities (i.e., no-feedback, auditory feedback, and vibrotactile feedback) when selecting a target using their eye gaze (as in Chapter 3), and guidance was turned on and off to see if there was an improvement in task performance. The results indicated that neither the feedback for the target selection nor the guidance for the movement improved the task performance of adult participants without impairments. However, visual analysis of the data indicated that the feedback increased the speed and accuracy of target selection and the guidance improved the movement efficiency for the adult participant with physical impairment and the child participants without impairments.

Chapter 5: Effectiveness of Haptic Feedback for Brain-Computer Interface Training.

In this chapter, the development of a BCI system that provided kinesthetic haptic feedback to users is described. The system passively moved their arm according to the detected movement intention. The effectiveness of the feedback was examined in several sets of BCI training sessions with ten adults without impairments, a child without impairments, and an adult with cerebral palsy. When learning to do motor imagery, it is recommended to perform repeated practice with feedback and rewards in order for the participants to acquire the skills required to control the BCI system. The Graz BCI training protocol, which is one of the most widely used BCI training protocols, detects the sensory motor rhythm induced by motor imagery and gives users a visual representation of how well they are performing the motor imagery. Instead of visual feedback in the BCI training, kinesthetic haptic feedback was tested to investigate whether it would be helpful in enhancing the brain activities associated with movement intention. BCI training using kinesthetic haptic feedback provided significantly more accurate classification than conventional visual feedback for ten adult participants without impairments. However, there was no significant improvement in how well the participants could perform the motor imagery with either the visual feedback or the haptic feedback over 12 runs of the BCI training. Responses to a NASA-TLX questionnaire revealed that the task with the haptic feedback had a lower workload than the task with the visual feedback. The child without impairments and the adult with physical impairment reported a higher workload than the adults without impairments. Kinesthetic haptic feedback for BCI was implemented in the integrated eye gaze and BCI system in a functional robotic task in Chapter 6.

Chapter 6: Integration of an Eye Gaze Interface and BCI with Biofeedback for Human-Robot Interaction

In this chapter, the eye gaze and brain signals were integrated as a human-robot interface to control a Lego robot, and the system was tested with five adults without impairments and an adult with cerebral palsy. The system provided vibrotactile haptic feedback about where participant's gaze was being tracked by the stationary eye tracker, and kinesthetic haptic feedback about how well brain activity was being detected. The task was knocking down one of two piles of blocks; the users selected a target block with their eye gaze and moved the robot towards the pile of blocks with their motor imagery. All adult participants without impairments achieved the robot control task with the haptic feedback faster than the task without feedback, with two of them showing significance, although time for the target selection in both conditions was about the same. Four out of five participants without impairments responded that the task had less workload in the haptic feedback condition than the task without feedback. Also, visual analysis indicated that the individual with physical impairments performed the task faster and reported less workload with the haptic feedback condition.

Chapter 2

Literature Review

This review begins with technologies that are used for play by children with physical impairments followed by a discussion about how assistive robots can be utilized for manipulative play with objects. The final part of this chapter includes the topic of human-robot interfaces that have been used by people with physical impairments for assistive robot control.

2.1 Technologies for Children with Physical Impairments to Access Play

Various technologies have been used as a means for children with disabilities to play. The review by Van den Heuvel, Lexis, Gelderblom, Jansens, and de Witte (2016) covered applications using Information and Communication Technology (ICT) and robots that support play for children with severe physical impairments. Three main groups of technology were identified, virtual reality (VR) systems, computer systems, and robotic systems. VR systems refer to applications that create simulated 3-dimensional environments on screen that make users feel as if they are immersed in a virtual environment. Computer systems referred to applications without the use of VR. Comparing VR systems with computer systems such as conventional video games, Van den Heuval et al., 2016 reported that VR systems primarily aim to stimulate and improve the user's motivation, body awareness, and orientation to space (Van den Heuvel et al., 2016). Some VR systems offer, not only visual feedback to the user, but also additional force/touch feedback from the control interface. For example, force/touch feedback in tasks such as carrying, moving and handling a virtual object can be achieved via controllers or gloves with a built-in vibrating motor (Wille et al., 2009). Van den Heuvel et al. (2016) noted an important difference between robots and VR systems or computer systems; robots can move in their physical environment, whereas the others are stationary systems. The capability of mobility of the robots presents an advantage over VR and computer systems, because limited mobility is a problem for children with severe physical disabilities. Use of a robot in manipulation tasks could give children access to play with physical objects and opportunities to learn and develop their cognitive skills through the manipulation of the physical environment.

2.2 Assistive Robots for Children with Physical Impairments to Access Play

Assistive robots enable manipulative play with objects for children with physical impairments. Ríos-Rincón et al. (2016) examined the potential of a robotic system affecting playfulness of children by using a Lego Mindstorms robot with four children with cerebral palsy. With three button switches for control (i.e., forward, left turn, and right turn), children maneuvered the robot and moved physical objects. All four children showed significant improvement in playfulness in a nonconcurrent, multiple baseline research design. Another robotic system, PlayROB, assisted in manipulation of Lego bricks (Gernot Kronreif et al., 2007; Prazak, Kronreif, Hochgatterer, & Furst, 2004). The children were able to use the robot to successfully pick up Lego bricks selected from a pile and place them on the desired location on the play area, and authors suggested that the children were developing spatial orientation skills. A joystick, 5-button input device, sip-puff switch, and single-button switches were used as control interfaces. Thus, children could use a control method based on their functional impairments or preferences. In Harwin et al. (1988), an industrial SCARA robot was modified for children with severe physical disabilities to perform play tasks such as stacking and sorting bricks. This system was a semi-automated, vision-based system. A button switch was used only as conformation for the task to “start” or “stop” and for the robot to “move” or “not-move”.

These assistive robot studies indicate that children with severe physical disabilities can experience physical manipulation through robot use and potentially learn in physical environments. The degree and type of disability of the participants varied depending on the individual, and operation of these robotic systems was not always possible (Kim Adams, Alvarez, & Ríos-Rincón, 2017), thus there is a need to improve the interfaces used to control the robots.

2.3 Human-Robot Interfaces

The human technology interface is an important component of assistive technologies. It should allow those with physical disabilities to access technology and to perform functional activities (Cook & Polgar, 2008). According to Tai, Blain, and Chau (2008), a human technology interface should comprise two main elements: (1) the physical sensors or input devices through which some form of functional intent, such as a physiological change or movement, is transferred into an electrical signal, and (2) a unit that processes and analyzes the input signal before subsequently generating a control signal. The same human technology interfaces that are used to control other assistive devices, can be used to control robots.

2.3.1 Button Switch Interface

One of most commonly used human-robot interfaces for people with impairments is a button switch. The button switch is the simplest type of switch and is essentially considered as a binary (on or off) device. With typical switches, it returns the "on" state only while the switch is pressed and remains in the "off" state otherwise. Use of multiple button switches allows robots to perform two and three-dimensional movements. For people with physical impairments, the switches can be placed in different anatomical locations, and the switches can have various shapes and sizes depending on the user's abilities. By using Lego Mindstorms, Ríos-Rincón et al. (2016) demonstrated that children could control the robot using three button switches for "forward", "left turn", and "right turn" by placing the switches beside anatomical sites that the children could easily control.

2.3.2 Joystick Interface

Another access method for people with disabilities is a joystick. There are two types of joysticks, proportional and discrete. A proportional joystick, commonly used with power wheelchairs (Cook & Polgar, 2014), returns continuous signals, which are adjustable in amplitude or level of the sent command. For instance, the farther the proportional joystick moves away from the starting point, the faster a wheelchair goes. On the other hand, discrete joysticks return discrete responses similar to an array of single button switches. These have only distinct directional command outputs. The "PlayROB" developed by G. Kronreif, B. Prazak, M. Kornfeld, A. Hochgatterer, and M. Furst (2007), aimed to assist children with severe disabilities for interaction with Lego bricks, was operated with four directional commands, plus a confirmation command, generated by a discrete joystick (and also a 5-button input device). Both proportional and discrete joysticks are suitable as a human-robot interface because the direction of robot movements can be intuitively controlled by the user. However, the user is required to have some degree of dexterous motion to operate the joystick efficiently.

2.3.3 Gesture-based Interface

Some studies have used gesture-based human-robot interfaces. A humanoid-type robot, COSMOBOT, developed by J. Brisben, D. Lockerd, and Lathan (2004), was designed for children with physical and cognitive impairments to motivate and actively engage children in their occupational therapy. The gesture-based interface, through wearable sensors on the body, allowed the robot to replicate the user's movement. For example, the robot would raise its arms in response to the user raising his/her arms, thus, the children could interact with the robot while performing the therapy exercise. This study reported that the robot made an impact on the occupational therapy goals of children with cognitive impairments.

Another example of a gesture-based human-robot interface is in a study conducted by Quintero, Tatsambon, Gridseth, and Jagersand (2015). The user could interact with a robot arm using gestures to perform pick-and-drop tasks. A seven-degrees of freedom (DOF) WAM robot was used as the robot arm, and Microsoft Kinect was used as a vision system to detect the user's gestures and locations of objects. An object was selected among several choices in the environment by the user's pointing gesture, and the robot arm grasped the selected object and dropped it onto a target location.

A gesture-based human-robot interface could be an intuitive and effective access method for robot control. However, it might be difficult for people with severe physical disabilities to make the distinct movements required for the system to discriminate the different gestures.

2.3.4 Eye Gaze Interface

In recent years, much research has been devoted to development of eye gaze-based human-robot interfaces. It is a common interface in assistive technology, for example, even though individuals may have little or no voluntary muscle control in their limbs, they have used an Augmentative and Alternative Communication (AAC) device with gaze input to communicate with others and interact with the world (Biswas & Langdon, 2011). Such devices generally provide an on-screen keyboard interface with text to speech output. Nguyen and Jo (2012) examined the control of a wheelchair by a wearable vision-based eye gaze interface equipped with 3-dimensional orientation sensors. The direction of the wheelchair was established by the user's eye gaze by selecting options on the wearable interface display for navigation. Besides the field of assistive technology, eye gaze technology has been utilized in research in psychology, marketing, and medicine (Ruhland et al., 2015).

Vision-based eye tracking is widely used for eye gaze interfaces. Vision-based eye gaze interfaces often require illumination of the eye with infrared light, and this makes the pupil stand out in a video image. The reflection off the cornea is used to estimate the direction of gaze. Much research utilizing eye gaze interfaces has been conducted in recent years, due to the increase in the processing power of computers and improvements in camera resolution which enable the detection of the eye gaze faster and more accurately than before (Chennamma & Yuan, 2013).

Arai and Yajima (2011) developed a feeding aid system using a robot arm integrated with an eye gaze interface. A small camera was mounted on the tip of the robot end-effector, and the view from the camera was displayed on a computer screen. The system enabled the user to select the desired food on the screen using eye gaze and the robot picked up the food and brought it closer so the user could eat it. In a study by Encarnação et al. (2017), a mobile robot was controlled by children by fixating their gaze on the robot commands on a computer display. Authors reported a positive impact on children with physical impairments to participate in academic activities.

Some research has pointed out challenges using eye gaze-based assistive technology with a clinical population. Amantis et al. (2011) found that children with cerebral palsy took longer and had less accuracy in gaze performance compared to children without impairments. Dhas, Samuel, and Manigandan (2014) stated that gaze interaction applications were not suitable for children who had too many involuntary movements because an eye tracker may lose accuracy in determining eye gaze direction.

The main problem for efficient gaze interaction is how to avoid unintended selections, called the Midas' touch problem (Møllenbach, Hansen, & Lillholm, 2013). One of the solutions for this problem is to employ dwelling, fixating the gaze for a prolonged period of time on the target option. Adjusting the dwell time has been used to give the system more tolerance in movements, and help users to be more successful accomplishing the gaze interaction (Isomoto, Ando, Shizuki, & Takahashi, 2018; Moiz Penkar, Lutteroth, & Weber, 2012). Additionally, when using an eye gaze interface to access technologies, feedback about where the tracker is interpreting the gaze is provided, such as a mouse pointer or cursor, for the selection of a graphic target options on a screen.

2.3.5 Brain-Computer Interface (BCI)

Recently, brain-controlled access pathways, often referred to as brain-computer interfaces (BCIs) or brain-machine interfaces (BMIs), have been proposed as a new means of device control, for assistive technology, including computers, augmentative communication and robots (McFarland & Wolpaw, 2011). BCIs are categorized into two methods: invasive and non-invasive. Examples of invasive methods are Electrocorticography (ECoG) and single-neuron recordings. ECoG records brain activity over the cortical surface of the brain, while single-neuron recordings detect activities within the cortex. Both techniques can record the activities over smaller regions of the brain than non-invasive methods, which provides higher spatial resolution, higher bandwidth, and higher signal to noise ratio (SNR). The drawback of the invasive methods is that surgical incision of the skull is required to implant electrodes, which results in problems in achieving and maintaining safe long-term use (Leuthardt, Schalk, Wolpaw, Ojemann, & Moran, 2004).

Non-invasive methods do not require a craniotomy and are safer than the invasive methods. Magnetoencephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and functional Near Infrared (fNIR) have shown success in the field of neuroscience. However, these techniques are still technically demanding and expensive. They require sophisticated equipment and can be operated only in special facilities (Ponce, Molina, Balderas, & Grammatikou, 2014).

Electroencephalography (EEG), another non-invasive method, measures the potential voltage over the scalp through electrodes. The EEG signals reflect the collective activity over large populations of neurons located underneath the electrodes. Even though it does not have the same spatial resolution, EEG is economical and portable, so it is the most widely used (McFarland & Wolpaw, 2011). EEG-based BCIs mainly rely on detecting two types of brain activity. The first type is evoked potentials, known as P300 evoked potentials (P300) and Steady States Visually Evoked Responses (SSVEP), and the second type is brain activity changes in the spontaneous oscillatory activity, known as Slow Cortical Potentials (SCP) and Event Related

Desynchronization (ERD) / Event Related Synchronization (ERS). The following sections describe each brain activity including the advantages and the disadvantages of each.

P300 Evoked Event Potentials

The P300 of visual/auditory evoked potentials is a positive waveform that appears 300ms after a stimulus is presented. This brain activity is generally measured from the midline centro-parietal regions and analyzed in the time-domain. The best-known application of P300 is the P300 speller developed by Farwell and Donchin (1988), where the columns and rows of an alphabet matrix are repeatedly flashed visually to the user. A P300 is elicited when the user is presented with intensification of the row and column containing the desired letter, upon which the user is gazing. Thus, the presence of the P300 can be used to detect the user's choice. The P300 speller achieved more than 70% classification accuracy in 5 out of 6 adult participants with ALS (Nijboer et al., 2008). In addition, 2 out of 3 adult participants with ALS achieved a comparable classification accuracy to participants without impairments (Sellers & Donchin, 2006). The letters in the P300 speller can be replaced with pictures or symbols (e.g., arrows or object selection buttons), so the P300 can be used as control interfaces for different purposes. Use of P300 does not require intensive training on the part of participants. However, visual/auditory stimuli to the user is always required.

Steady State Visually Evoked Potentials (SSVEP)

SSVEP is a brain response to visual stimulus (e.g., flashing LED or a phase inversing checkerboard) (Daly et al., 2013). SSVEP responses in the occipital lobe appear as peaks at frequencies matching that of the frequency of the visual stimulus. SSVEP are options for people who have eye acuity but cannot move their eyes (Allison et al., 2008). Wang, Wang, Gao, Hong, and Gao (2006) demonstrated that with SSVEP-based BCIs for environmental control, 10 out of 11 adult participants with SCI were able to use the BCI system. One drawback to SSVEP is that it may result in epileptic seizures due to photosensitivity. Another drawback is that control interfaces for SSVEP can contain only a limited number of selection choices. A major advantage of SSVEP is that it does not require intensive training sessions (Cruz, Haddad, Bastos-Filho, & Adams, 2019).

Slow Cortical Potentials (SCP)

SCPs are slow voltage changes spontaneously generated over the cortex. They are time locked, response-specific events such as excitement, relaxation, or movement. Negative SCPs are associated with motions as well as motor imagery, and positive SCPs are related to response inhibition and relaxation. The duration of the SCP response is generally between 300ms and several seconds (Birbaumer et al., 1999). SCPs can be evaluated with a simple time-domain waveform analysis. Birbaumer, Hinterberger, Kubler, and Neumann (2003) examined SCP-based BCIs used for spelling and controlling environmental devices and demonstrated that the devices achieved a classification accuracy of 70%. However, the authors commented that it required several training sessions to achieve the high classification accuracy. Use of SCP training generally requires several weeks or even months which can be a major drawback for SPC-based BCIs (Ponce et al., 2014). Another drawback is that the slow response time compared to ERD/ERS-based BCIs.

Event Related Desynchronization (ERD)/ Event Related Synchronization (ERS)

Event Related Desynchronization (ERD) and Event Related Synchronization (ERS) responses can be voluntarily induced by the user (e.g., during imagination of kinematic body movements and actual body movements) (Ponce et al., 2014). Sensory processing of motor behaviour shows a decrease of spectral amplitudes of the alpha rhythm in the range from 8 to 13 Hz, as originally reported by Berger (1931). This decrease of oscillatory activity is known as ERD (Pfurtscheller & Aranibar, 1979). The opposite, namely the increase of spectral amplitudes of beta rhythm in the range from 13 to 26 Hz, is known as ERS (Pfurtscheller & Neuper, 2010). ERD/ERS can be observed on the contralateral hemisphere to the movement for both motor execution and motor imagery and can be analyzed by the bandpower at frequencies within the range of alpha and beta rhythms. This allows motor execution or motor imagery to translate to control signals for devices.

ERD-based BCIs have been developed to test various devices, and tested by people who do not have disabilities. Chatterjee, Aggarwal, Ramos, Acharya, and Thakor (2007) developed ERD-based BCIs as input devices for real-time 2-dimensional cursor control and tested it with 3 adult participants without impairments. They achieved 87% classification accuracy when the participants made physical movements and 57% classification accuracy when the participants did motor imagery. A study by Tang et al. (2016) investigated whether self-induced variations of the ERD/ERS can be useful as control signals for an upper-limb exoskeleton. The classification accuracy during motor imagery tasks (i.e., rest and move) with and without the exoskeleton was evaluated with four adults without impairments. Their tests achieved a mean classification accuracy of 87.37% for the tasks with the exoskeleton and 84.29% for the tasks without it.

Since the use of ERD/ERS can be a potential solution for individuals with little or no voluntary muscle control to access computers or other devices, much research related to ERD/ERS-based BCIs has been conducted to date. In Cincotti et al. (2008), 14 adult participants without impairments and 14 adult participants with spinal muscular atrophy or Duchenne muscular dystrophy successfully performed 2-dimensional cursor control with motor imagery. The average classification accuracy achieved was 80% for the participants without impairments and 62% for participants with impairments. López-Larraz, Montesano, Gil-Agudo, Minguez, and Gil-Agudo (2014) evaluated the ERD of 6 adult participants without impairments and 3 adult participants with SCI during upper limb movement. The classification accuracy of the BCI system was 75% for movements for the participants without impairments, and the classification rates of ERD for the participants with SCI were similar to the participants without impairments.

In the study of Daly et al. (2014), ERD induced by motor imagery of adult participants with CP and adult participants without impairments were compared. For both groups, ERD was successfully detected, however, ERD levels for participants with CP were significantly lower than for participants without impairments. In another study, 14 adult participants with CP tried ERD-based BCIs and SSVEP-based BCIs (Daly et al., 2013). They found that 6 of the 14 participants could control the ERD-based BCI at above significant levels of accuracy, and 3 of the 14 participants could control the SSVEP-based BCI at above significant levels of accuracy (one user could control both methods at significant levels of accuracy). Daly et al. (2013) commented that the reason that results of the SSVEP-based BCI were less effective than the ERD-based BCI was that spasticity and the need of a neck rest by people with CP strongly hindered the ability to make good connections at the occipital electrodes.

ERD has also been studied in the pediatric population. The frequency of sensorimotor rhythms in children is less than an adult's sensorimotor rhythms and varies depending on the child's ages (Berchicci et al., 2011). Lee et al. (2012) investigated the feasibility and test-retest reliability of the ERD/ERS in 5 child participants without impairments and 7 child participants with CP. ERD/ERS during reach-and-grasp hand movements were repeatedly measured and obtained excellent reliability with a level of significance ($p < 0.005$) for both participant groups. In addition, Lee et al. (2012) compared the cortical activation pattern during actual movement between participants without impairments and participants with CP. The results showed that the cortical activity pattern was primarily localized over the motor cortex in participants without impairments, whereas in participants with CP the cortical activation pattern was more diversified over the motor cortex, parietal cortex, and occipital areas.

ERD/ERS is a promising method for robot control. Among the various EEG brain activities, only ERD/ERS and SCP correlate with motor execution and motor imagery. These responses are spontaneous and do not require external stimulus to elicit. According to a review paper from Moghimi, Kushki, Guerguerian, and Chau (2013), SCP was most frequently used in BCIs in the past decade. However, because of its slower response and longer training period, ERD/ERS-based BCIs superseded the SCP-based BCIs for computer and robot control today.

In summary, some studies demonstrated successful implementation of the ERD/ERS-based BCI systems in robot control for people with physical impairments (Daly et al., 2014; Dodd, Imms, & Taylor, 2010), though some studies found that the use of BCI for those population would be more challenging than for users without impairments (Berchicci et al., 2011). This suggests that that careful implementation requires determining the frequencies and scalp locations of each person's sensorimotor rhythms in order to measure reliable ERD/ERS from individuals with impairments. Even though the ERD/ERS-based BCI may not be always effective for all the populations, it is a potential method for potential robot access pathways for people with impairments.

2.3.6 Haptic Interface

Robots can be haptics-enabled, which can provide several functions in a human-robot interface. First, it can give the user the experience of physical object manipulation, which can assist in the acquisition of perceptual skills. Haptic interfaces generate kinesthetic touch sensations by conveying forces, vibrations, or motions to the user (Jafari, Adams, & Tavakoli, 2015; Krebs, Hogan, Aisen, & Volpe, 1998) and can therefore enhance exploration of the environment (Demain, Metcalf, Merrett, Zheng, & Cunningham, 2013). A haptic-enabled robotic system can operate in two modes, unilateral or teleoperation. In unilateral manipulation a user directly holds a haptics-enabled robot/interface and interacts with the environment. In telemanipulation a user operates a user-side robot/interface that controls another robot to interact with the environment (task-side robot) (Abbott, Marayong, & Okamura, 2007). Unilateral manipulation is intuitive as the user applies natural hand-eye coordination, whereas telemanipulation has the benefit of remote operation. Telemanipulation is the configuration that would be most beneficial to children with disabilities, as the user-side device can be mounted on their wheelchair or supported chair, and the task-side robot can be in the play environment. In a study by Becerra (2017), a haptic-enabled interface was used to teleoperate a task-side robot to explore properties of objects, such as size, shape, or texture. Comparing with the exploratory performance using the hands, adults without impairments, typically developing children, and an adult with physical impairments showed similar or better performance at identifying properties using the haptic interfaces.

Another benefit of haptic-enabled interfaces is that the haptic feedback capability can assist in the operation of the interface for people with physical impairments by applying features like position/force scaling and movement adjustments at the task-side device. A haptic telerobotics platform was tested by an adult with CP in a physical play environment (Atashzar et al., 2015). The haptic capabilities of the system allowed forces occurring at the task-side robot to be felt at the user-side robot, and the system also scaled up the user's limited range of motion and made the user's movements smoother. The involuntary component of the hand motion, which has a high-frequency in comparison with the voluntary component of the hand motion, was filtered out. Plus, movements that passed through the filter were dampened by a factor that the user chose as comfortable. This platform enabled the individual with CP to accurately perform a sorting task requiring large-scale motions.

Haptic interfaces can also to help with guidance by creating virtual fixtures (VFs), which are software-generated forces applied by the robotic interface (Abbott et al., 2007). Guidance VFs (GVFs) assist in guiding the robot along a desired pathway, while Forbidden Region VFs (FRVFs) help to keep the robot inside (or outside) a defined region. In preliminary work for this dissertation, a robotic system with FRVFs was developed and tested with 10 nondisabled participants and an individual with spastic cerebral palsy (Sakamaki, Adams, Gomez, et al., 2017). The system successfully restricted the users' hand movements inside a defined region during robot operation so the users could rely on the VFs to move their hand along the defined region to reach the target.

A computer vision system was used for defining the location of the VFs in a play environment. This system was fast and robust enough to be used in real-time during a pick and place task.

Another application of haptic interfaces is as biofeedback to enable users to learn how to modify physiological activity. Haptic feedback can help users to physically engage, pay attention, and reinforce actions (Menelas & Benaoudia, 2017). Vibrotactile haptic feedback has been utilized to improve navigation and orientation in order to reduce workload of visual and auditory systems, an example is vibration when touching the screen of a smartphone (Gleeson & Provancher, 2013). Kangas et al. (2014) conducted a study of combining gaze gestures with vibrotactile haptic feedback that gave confirmation of the different eye gaze gestures. The test with 12 adult participants revealed that gaze interaction with the vibrotactile haptic feedback was significantly faster and preferred over the no haptic feedback condition. Pichiorri et al. (2011) found that motor imagery skill can be enhanced in BCI performance with biofeedback such as visual, auditory, or vibrotactile haptic feedback. In a study by Chatterjee et al. (2007), they implemented a BCI-based cursor position control, which was based on the intention of left or right arm movement. Feedback was shown visually as well as transmitted haptically to the user's upper limb. The results indicated that vibrotactile haptic feedback improved the performance of BCI operation more than visual feedback alone.

Kinesthetic haptic guidance or feedback has also been utilized as biofeedback. In rehabilitation, kinesthetic guidance can be used to demonstrate and practice movements for people with physical impairments (Dodd et al., 2010; R Brewer, K McDowell, & Worthen-Chaudhari, 2007). An ERD/ERS-based BCI-driven robot for upper limb rehabilitation was tested with hemiparetic stroke patients for restoration of motor control, and results indicated that kinesthetic haptic feedback based on their movement intention was effective in restoring some motor control (Kai Keng Ang et al., 2009). Gomez-Rodriguez et al. (2010) examined the effectiveness of kinesthetic haptic feedback on brain activities associated with ERD/ERS. The authors examined brain activity during robot-assisted physical therapy with kinesthetic haptic feedback based on movement intention. The results revealed that passive movements made by the kinesthetic haptic feedback could induce brain patterns similar to those observed during motor imagery, and hence, improve the BCI classification accuracy.

2.4 Summary

Through this literature review, numerous human technology interfaces for robot control were identified. However, most of the robotic systems only allow one human technology interface at a time. The human technology interface could be improved by combining different access options as possible to meet demands of people with different impairments (Van den Heuvel et al., 2016). In addition, studies to access play using robots have only been done using interfaces that require some physical movement. In this dissertation a human-robot interface combining eye gaze and brain signals was developed.

An eye gaze interface only requires eye movement to access and operate, which could be an intuitive method for users to select the object of interest they wish to manipulate with a robot. However, in the eye gaze robotic applications above, the users had to look at a computer screen to fixate their gaze on the robot commands (Arai and Yajima (2011); this requires the user to shift their gaze between the screen and the robot play environment, which is distracting for child users, and can cause the eye tracker to decalibrate (i.e., lose track of where the eyes are). To directly interact with the physical environment by gaze, alternatives to the visual feedback are needed, and auditory and vibrotactile feedback are promising.

A BCI has the potential to be an intuitive method for people with physical impairments to generate movement of a robot. Even though the performance accuracy of the BCI varied from study to study above, and BCI is one of the least accurate human-robot interfaces summarized in this chapter, the advantage is that it requires no physical movement. To enhance BCI performance, feedback about the signal strength is needed, as noted in the studies above. Kinesthetic haptic feedback sounds promising to help users enhance their BCI signals and operate the robot accurately and efficiently in an off-screen situation.

A human-robot interface combining eye gaze and brain signals could allow the user to select objects to manipulate and then control the robot by their motor imagery in the physical environment, without the need for a computer display. Feedback can help to make the interactions more accurate. This type of integrated interface could lead to improved control of robots in physical environment play activities for people with impairments.

Chapter 3

Effectiveness of Different Biofeedback Modalities for Improving On-screen and Off-screen Eye Gaze Interaction

3.1 Introduction

The experience of object manipulation in the physical environment has a large influence on cognitive development in children (Gibson, 1988; Musselwhite, 1986). Cognitive development refers to the development of children in terms of thinking, resolving, learning, feeling, and knowing the environment (Bjorklund, 2005). Physical manipulation has been identified as a critical motor experience that enables children to learn skills, such as the emergence of symbols, referential communication and the understanding of relations between objects (Piaget, 1962). For children who have complex physical disabilities that prevent them from reaching and grasping objects, one of the biggest concerns is lacking opportunities for meaningful manipulation tasks, often in the context of play activities (Taylor et al., 2010). This lack of opportunities may negatively affect the progressive development of their learning skills and mental growth (Bjorklund, 2005).

Robots have been utilized by children who have physical impairments to access play activities (K. Adams, Rios, & Alvarez, 2017). Robot systems can behave like extended arms, allowing children to reach what they otherwise could not reach or probe what they otherwise could not probe. However, these technologies often still require a certain degree of physical ability to access and to operate, such as using switches or joysticks. Eye gaze has been used to control assistive technology for many years (Cook & Polgar, 2008), and recently, the cost of eye trackers has gone down, making it a feasible access method to control robots.

The most common setup for eye gaze is to have the user fixate on graphic target options on a screen (called on-screen herein). The users generally rely on feedback about where the tracker is interpreting the gaze, such as a mouse pointer for the selection. For example, individuals with severe physical impairment can generate synthesized speech for communication by selecting symbols on a screen (Biswas & Langdon, 2011). Arai and Yajima (2011) developed a feeding aid system using a robot arm integrated with an eye gaze interface. The user gazed at the desired food on the screen and then the robot picked up the food to bring it closer to the user. In Encarnação et al. (2017), children controlled the LEGO Mindstorms robot (Lego A/S, Billund, Denmark) with an eye gaze-tracking system that enabled children with physical impairment to participate in academic activities. Simple robot commands were displayed on a computer screen and users controlled the robot by fixating their gaze on the command. The system demonstrated positive impact on children with physical impairment, but Encarnação et al. (2017) pointed out that it required considerable effort for children to look at the screen to select the robot command and then look at the robot to check its effect. This forced the user to keep changing their visual attention during the tasks and added a layer of complexity.

When using eye gaze to control robots in the physical environment, it would be better if the user did not have to look at a computer screen to select robot movements. Using head-mounted eye trackers is one way to accomplish this (Ryan, Duchowski, & Birchfield, 2008). For instance, eye gaze estimation using a head-mounted tracker helped to reveal how humans gather information from their environment and how they use that information in motor planning and motor execution (Land & Hayhoe, 2001). Galante and Menezes (2012) developed a head-mounted eye tracker enabling the system to estimate gaze position in the physical environment by mapping between the camera frame view and actual gaze direction using geometric calibration techniques. However, these are expensive, and some people do not tolerate wearing them.

A stationary eye gaze interface could be used without a computer screen to select objects in a physical environment if geometric calibration techniques are used (called off-screen herein). However, to use it, feedback about where the tracker is interpreting the gaze is crucial. For robot control in the physical-world, visual feedback of a mouse pointer on a screen is not possible, thus, other kinds of feedback are needed.

The feasibility of alternative feedback modalities for gaze applications on-screen have been investigated (Burke et al., 2006; Majaranta et al., 2006; Pomper & Chait, 2017; J. Rantala et al., 2017). Majaranta et al. (2006) explored a combination of auditory and visual feedback in eye typing. The authors found that the visual auditory feedback significantly improved user text entry speed and satisfaction compared to visual feedback alone. Boyer, Portron, Bevilacqua, and Lorenceau (2017) investigated whether real-time auditory feedback of eye movement improved an on-screen target tracking task in the absence of visual feedback. Although large individual differences were observed, the auditory feedback did modify the oculomotor behaviour and improved task performance. Kangas et al. (2014) compared off-screen gaze interaction using gaze gestures (looking right then left to activate a command) with vibrotactile feedback and no feedback. All 12 participants performed the gaze interaction faster and preferred the vibrotactile feedback over no feedback. Auditory and/or vibrotactile feedback could be feasible ways for users to confirm their gaze interaction when using a robot in a physical environment for play.

Some research has pointed out challenges using eye gaze-based assistive technology with a clinical population. Amantis et al. (2011) found that children with cerebral palsy responded more slowly and less accurately in gaze performance compared to children without impairments. Dhas et al. (2014) found that gaze interaction applications were not suitable for children who had too many involuntary movements because the eye tracker lost accuracy in determining eye gaze direction. The main challenge for efficient gaze interaction is how to distinguish between gaze intended to gather visual information versus gaze to activate a specific command. This problem often results in unintended selections, which is called the Midas' touch problem (Møllenbach et al., 2013). One solution for this problem is to employ dwelling, requiring the user to fixate gaze for a prolonged period of time on the target option. A typical dwell time for eye typing using a screen based eye gaze system is approximately 0.5 to 1 seconds (Bednarik, Gowases, & Tukiainen, 2009). Adjusting the dwell time or the diameter of the target acceptance size may allow for more tolerance in movements, and help users to be more successful accomplishing the gaze interaction.

On-screen gaze interaction is well established and researched, however, off-screen gaze interaction using dwell selection, such as selecting an object in a physical play task scenario for the robot to more towards, is novel in the field of assistive technology. Auditory and haptic feedback could help users to be more accurate at target selection, but appropriate settings for the device features need to be examined. In this study, we developed a gaze interaction system that maps eye gaze direction between the reference coordinate frame of a stationary eye tracker and coordinate frames of objects in on- and off-screen environments. The effect of different feedback modalities (i.e., visual feedback, no-feedback, auditory feedback, and vibrotactile feedback) about where the eye tracker determined the eye gaze to be fixed in a target selection task, and the effect of different target sizes, were examined.

The research questions addressed in the study were:

(1) How do the speed and success of gaze interaction differ between on-screen and off-screen conditions?
(2) Which feedback modalities and target size make the gaze-based target selection faster and more successful?
(3) What is the feedback preference of the participants in the on- and off-screen gaze interaction?

3.2 Methods

3.2.1 Participants

Ten university students without physical impairment, three males and seven females, aged from 22 to 38 (26 ±4.1), participated in the study (called A1-A10 herein). The system was also tested by two adults with quadriplegic cerebral palsy (a 52 year old female and a 33 year old female, called B1 and B2, respectively), three children without impairments (a 10 year and 2 month old boy, a 7 year and 10 month old girl and a 6 year and 4 month old girl, called C1, C2 and C3, respectively), and a child who had right side spastic hemiplegic cerebral palsy (a 7 year and 4 month old boy, D1). Participants B1 and B2 have mixed high and low muscle tone and involuntary movements and perform self-mobility by using a powered wheelchair. B1 is affected by strabismus and has difficulty focusing on objects with both eyes simultaneously, while B2 has no visual impairment. The participant D1 has no visual impairment, however, he was diagnosed with Attention Deficit Hyperactivity Disorder (ADHD) which may cause reduced gaze concentration (greater spread of vertical and horizontal eye movements) (Munoz, Armstrong, Hampton, & Moore, 2003). Ethical approval was received from the local Health Research Ethics Board Health Panel at the University of Alberta.

3.2.2 Design

There were two experimental screen conditions in the study: a gaze interaction task with a computer screen, called on-screen condition, and a gaze interaction task with the physical environment, called off-screen condition. In each screen condition, different target size and feedback modalities were examined.

3.2.3 Experimental Setup

The system diagram of the on- and off-screen experimental set up is shown in Figures 3-1 and 2. A Windows-based computer and a stationary eye tracker, Tobii eye tracker 4C (Tobii Technology, Danderyd, Sweden), and external devices for feedback modalities were the basic components for both the on- and off-screen conditions. A 19-Inch LCD monitor (42cm × 24cm) was added for the on-screen condition, and a computer vision system was added for the off-screen condition. The eye gaze acquisition was performed in MATLAB (MathWorks, Nadick, MA, USA). The feedback system, computer vision system, and interconnecting of systems were programmed in LabVIEW (National Instruments, Austin, TX, USA). Details of each component are explained below.

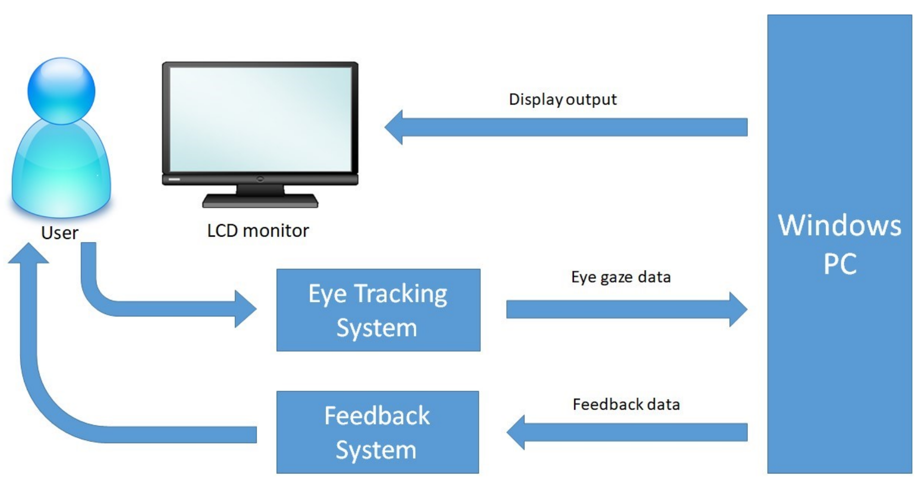

Figure 3- 1 Schematic diagram of the system in the on-screen experiment

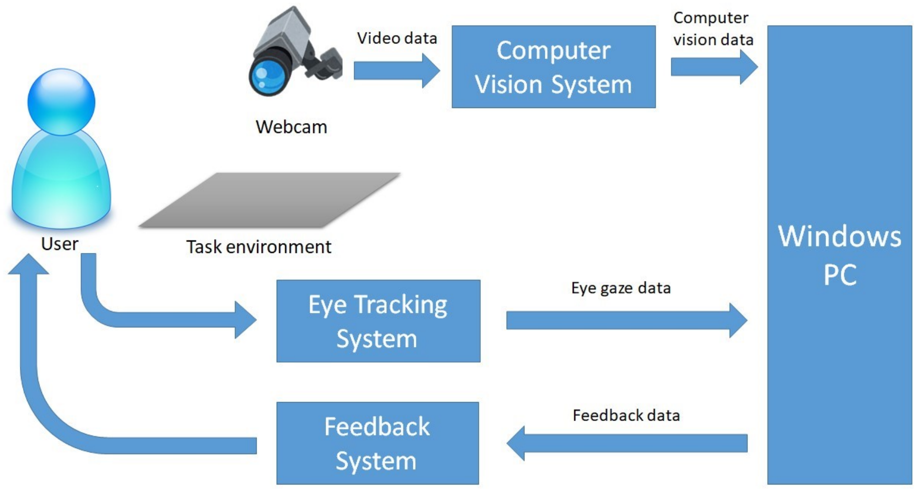

Figure 3- 2 Schematic diagram of the system in the off-screen experiment

Eye Gaze Acquisition System

The Tobii eye tracker 4C was used as an eye tracking interface. The eye tracker was placed in front of the task environment and connected to a Windows PC with a sampling frequency rate of 90Hz, in order to monitor fixation of the gaze during the gaze interaction. The dwell time was set to 1.5 seconds in all the conditions. A longer dwell time than typical was selected in this study to make sure participants had enough time to select the target during the off-screen condition, based on pilot testing of the system. When the participant fixated their gaze on the target for 1.5 seconds, the system recognized it as the target that the participant desired to select. 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.

Feedback System

In the on-screen condition, the LCD monitor showed a standard arrow-shaped mouse pointer as the visual feedback. This pointer was controlled by the participant's eye movement. There was also auditory and vibrotactile feedback used in both on- and off-screen conditions. A USB stereo sound adapter was used to generate the output of a 100 Hz sine wave for these feedback modalities. For the auditory feedback, the sine wave was outputted to earphones that the participants wore, and for the vibrotactile feedback, the wave was sent to an amplifier to drive a vibration motor (Bit Trade One, Kanagawa, Japan) on which the participants placed a fingertip during the trials. Both auditory and vibrotactile feedback were initiated when the participant's gaze was within the set target acceptance size radius, and the amplitude of the feedback increased in proportion to the time the gaze was on the target as an indication of the target being selected.

Computer Vision System

The computer vision system used in the off-screen condition was a USB webcam (Dynex, Richfield, MN, USA) (See Figure 3-2). The location and colour of each object in the task environment were detected by an object recognition program coded in LabVIEW. Since the Tobii eye tracker 4C was designed for gaze interaction in two dimensional space, the participant's gaze was mapped into the two dimensional plane of the task environment. The gaze mapping was done by the following steps:

(1) A template on which four calibration points were printed was placed in the task environment.
(2) The calibration template was captured with the webcam mounted above. Then, the centre point of each calibration point was computed by the object recognition program.
(3) The participant fixated their gaze at each calibration point in turn. The gaze position detected by the eye tracker at each calibration point was collected.
(4) Each gaze position was mapped to each calibration point on the task environment using a projective homogeneous transformation.

A homography is a perspective transformation of a plane, that is, a reprojection of a plane from one space into a different space as shown in Figure 3-3. For the homography, the relationship between two corresponding points can be written as (Szeliski, 2011):

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{3.1}$$

Where $[x \quad y \quad 1]^T$ represents the gaze position obtained by the eye tracker when the participant is looking at a calibration point, $[x' \quad y' \quad 1]^T$represents a calibration point in the task environment obtained by the computer vision system, and the 3 x 3 matrix represents a homogeneous transformation.

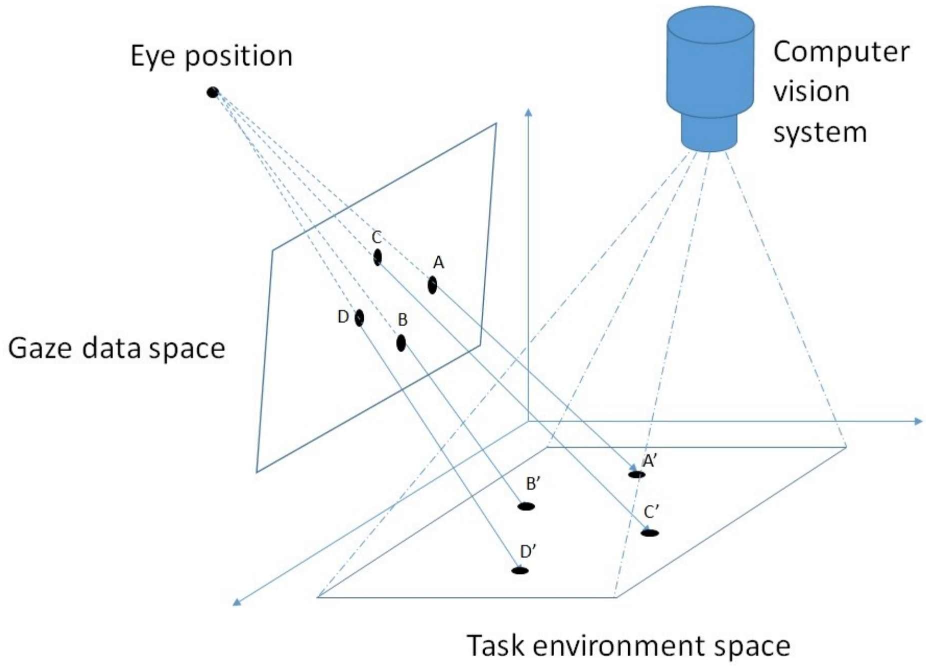

Figure 3- 3 Two corresponding points on different space are converted by a homography

3.2.4 Procedures

On-screen Condition

There was a run of twelve trials for four different feedback conditions (i.e., visual feedback, no-feedback, auditory feedback, and vibrotactile feedback), and the order of runs was counterbalanced. The participant sat at a distance of 60 cm from the computer monitor. At the beginning of the on-screen condition, the Tobii gaze tracking utility software was used to calibrate the participant's eye gaze.

For the experiment, four circles with a diameter of 3 cm were displayed (See Figure 3-4). The target was a blue circle, and the remaining stimuli were red circles. The target location was randomized within the 4 circles, and the participants needed to fixate their gaze on the new target each time. A fixation cross was displayed at the center of the screen during each inter-trial interval. The target acceptance size was changed randomly in the 12 trials. The diameter of the target acceptance sizes tested for the adult participants without impairments were: 3 cm, 6 cm, and 9 cm. The diameter of the acceptance sizes used for the adult participants with physical impairments and the child participants with and without physical impairments were: 6 cm, 9 cm, and 12 cm. The sizes were larger because the 3 cm diameter was too difficult for these population groups to achieve success in selecting, according to their results in pre-experiments.

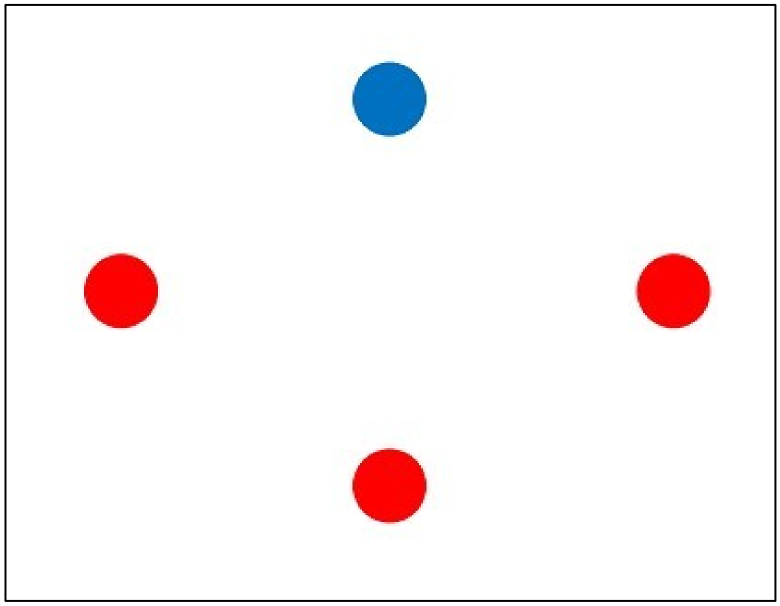

Figure 3- 4 Four circular targets displayed on the LCD monitor for the on-screen experiment

Off-screen Condition

There was a run of twelve trials for three different feedback conditions (i.e., no-feedback, auditory feedback, and vibrotactile feedback), and the order of runs was counterbalanced. The target acceptance sizes, which were the same dimensions as in the on-screen condition (i.e., 3, 6, and 9 cm for adult participants without impairments and 6, 9 and 12 cm for the adult participants with physical impairments and the child participants with and without physical impairments), were changed randomly during each trial.

The dimensions of the task environment were set to resemble the 19 inch LCD monitor used in the on-screen condition. The environment where the targets were placed was located 60 cm away from the participants, and the eye tracker was placed in front of the targets as shown in Figure 3-5. At the beginning of the off-screen condition, the calibration procedure using the computer vision system was performed as described above. For the experiment, an image of four printed circular objects with different colours (i.e., red, green, yellow, and blue) with a diameter of 3 cm was placed in the task environment. The four different colours were used in this screen condition because the targets were fixed, and not able to change colour like they did in the on-screen condition. The participants were given verbal instructions from the computer on which coloured object they needed to fixate their gaze during the task. There was a cross at the center of the task environment for the participants to return their gaze between the target selections.

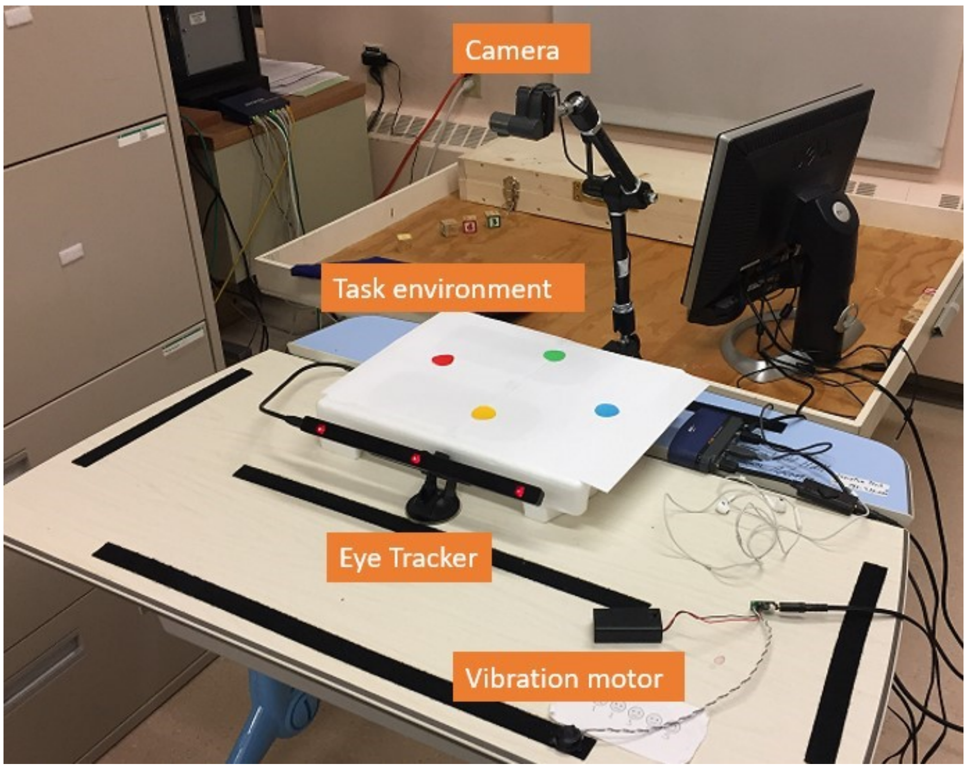

Figure 3- 5 Four circular targets in the task environment for the off-screen experiment

At the end of the session, the participants answered a questionnaire where they were asked to rank the feedback modalities according to their preference. The participants were also asked if they had any comments.

3.2.5 Measurements and Analysis

The dependent measures were as follows:

- **Target selection time:** To compare which condition was faster, the time from the task cue until the target was selected by the gaze was measured in milliseconds.

- **Timeout error rate:** To compare success at selecting targets, the timeout error rate was calculated, i.e., when the participant could not select the target within 10 seconds. The timeout error rate was the proportion of trials when the task timed out.

To examine the target selection time of the 10 adult participants without impairments (A1-A10), the Shapiro-Wilk normality test was performed first to check if the data were normally distributed. If the data were normally distributed, a two-way repeated-measures analysis of variance (ANOVA) was applied with the following factors: factor 1 was the target acceptance size (3 levels: 3, 6, and 9 cm); and factor 2 was feedback modality (with 4 levels for the on-screen condition: visual feedback, no-feedback, auditory feedback, and vibrotactile feedback, and 3 levels for the off-screen condition: no-feedback, auditory feedback, and vibrotactile feedback). A probability of $p < 0.05$ was considered significant.

For the adult participants with physical impairments (B1 and B2), child participants without impairments (C1, C2, and C3), and the child participant with physical impairments (D1), individual task performance was evaluated based on visual inspection and descriptive statistics because of the small, heterogeneous sample.

To compare on- and off-screen conditions overall, an overall average target selection time was calculated per participant group by averaging the target selection times of all the feedback modalities and the acceptance sizes in both screen conditions. Also, the average timeout error rates in each experimental condition were calculated and compared between the participants for each target size and feedback.

3.3 Results

3.3.1 Target Selection Time

Adult participants without impairments

Results of the target selection time for the adult participants without impairments in the on- and off-screen experiments are shown in Figure 3-6 (a) and Figure 3-6 (b), respectively. Target acceptance size had a significant effect for both the on- and off-screen conditions ($F[2, 18] = 44.77$, $p = 0.001$ for on-screen and $F[2, 18] = 30.84$, $p = 0.001$ for off-screen). Feedback modality was also significant (F [3, 27] = 4.40, p = 0.012 for on-screen and F [2, 18] = 6.588, p = 0.019 for off-screen). The main effects were qualified by interactions between target acceptance size and feedback modality only for the on-screen condition, but the interaction did not reach significance for the off-screen condition (F [6, 54] = 5.186, p = 0.008 for on-screen and F [4, 36] = 2.80, p = 0.091 for off-screen).

According to the post hoc Tukey test for the paired comparison, the acceptance size of 3 cm differed significantly from other acceptance sizes for both the on- and off-screen conditions. In both screen conditions, the no-feedback was significantly different from other feedback modalities. Lastly, the ANOVA showed a difference in the screen conditions where the target selection time in the off-screen condition was significantly longer than in the on-screen condition (F [1, 9] = 62.541, p = 0.0001). Note that the visual feedback modality was excluded for comparison because it was only presented for the task in the on-screen condition.

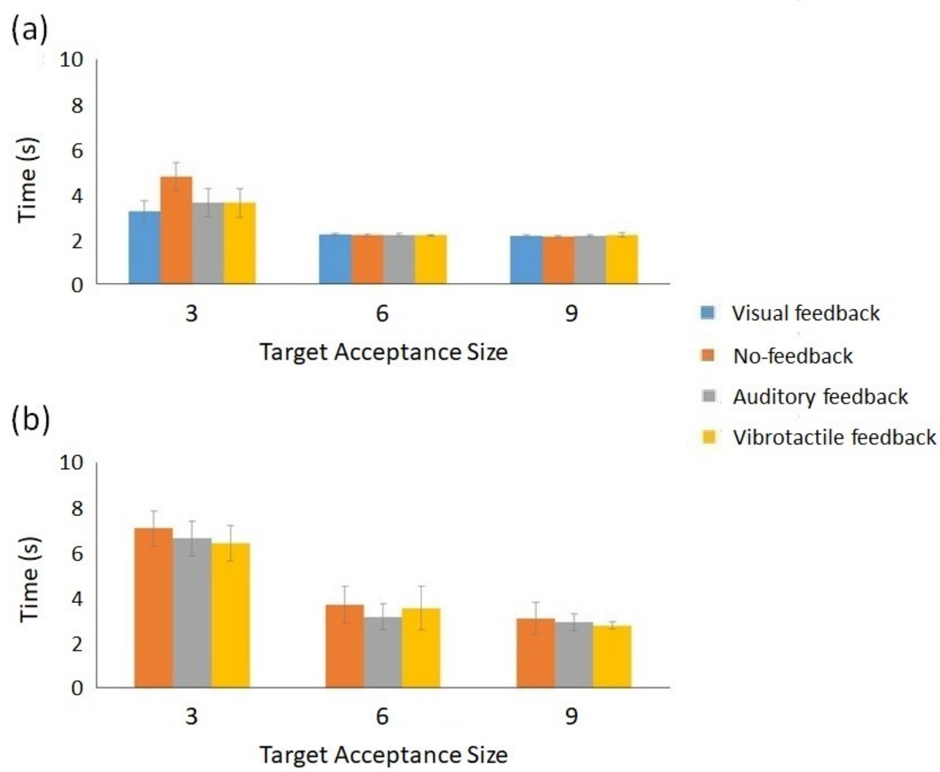

Figure 3- 6 Target selection time with the different target acceptance size and feedback modalities for the ten adult participants without impairments for (a) the on-screen experiment, and (b) the off-screen experiment

Adult Participants with Physical Impairments

The results of the on- and off-screen conditions for the two adults with physical impairments, B1 and B2, are shown in Figure 3-7 (a) and Figure 3-7 (b). Visually inspecting the graphs, it appears there was a performance difference between feedback modalities in the 6 cm target acceptance size for B1 in the on-screen condition. The visual feedback and the no-feedback selection time appear longer than those for vibrotactile and the auditory feedback. However, not much difference was observed between feedback modalities in all the target acceptance sizes for B2. For the off-screen condition, the data for B1 appears to show that the target selection time increased as the target acceptance size got smaller. Also, the target selection time in the no-feedback condition with the 6 cm target acceptance size appears to be longer than other feedback modalities. There seems to be no trend in the data for B2 in terms of the performance in each of the feedback modalities in both screen conditions. The overall average target selection time for the off-screen condition was 43.4% longer than the on-screen condition for B1 and 24.3% longer for B2.

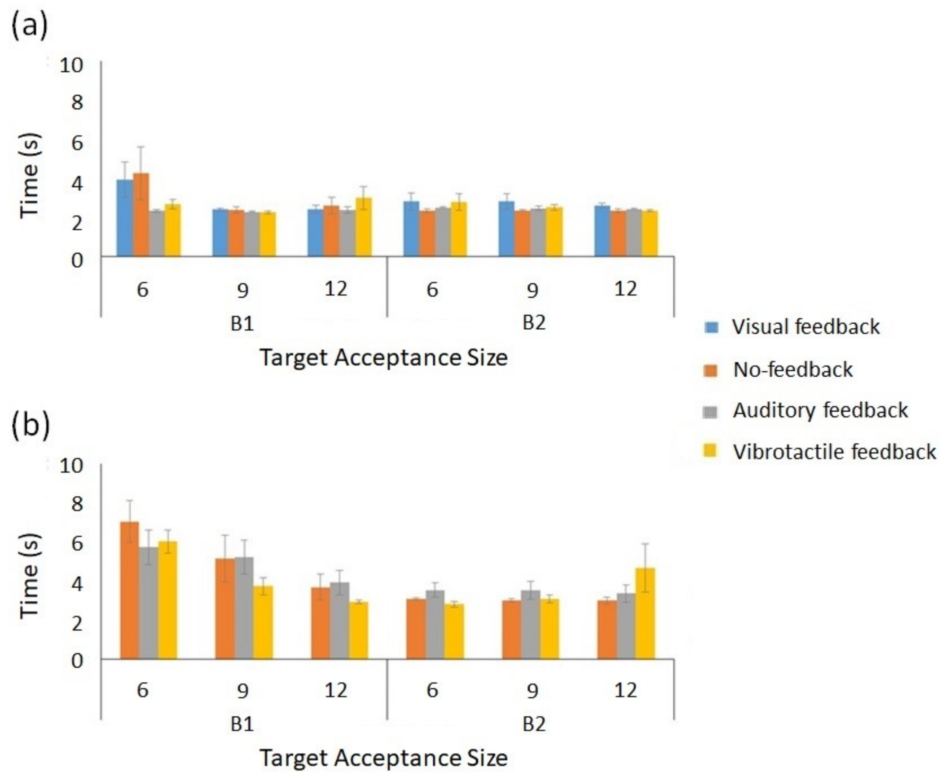

Figure 3- 7 Target selection time with the different target acceptance sizes and feedback modalities for the two adult participants with physical impairments for (a) the on-screen experiment, and (b) the off-screen experiment

Child Participants without impairments

Visually inspecting Figure 3-8 (a), participant C1 seems to have a trend that the longer selection time is with the auditory feedback in the on-screen conditions. However, it does not appear that the auditory feedback was clearly longer than other feedback modalities in the off-screen condition (see Figure 3-8 (b)). The on-screen condition for C2 appeared not to have much difference in the target selection time among the feedback modalities. On the other hand, no-feedback was greater than the other feedback modalities for all the target acceptance sizes in the off-screen condition. Also, the target selection time appeared to increase as the acceptance size got smaller. From the data for C3, the feedback that had the shortest selection time was the visual feedback in the on-screen condition. The no-feedback modality was longer with the target acceptance size of 6 cm in the both on- and off-screen conditions. In general, the target selection time in the off-screen condition took longer than in the on-screen condition, though this was not statistically tested. The average target selection time increased by 12.1% for C1, 61.4% for C2, and 40.9% for C3 from the on-screen to the off-screen conditions.

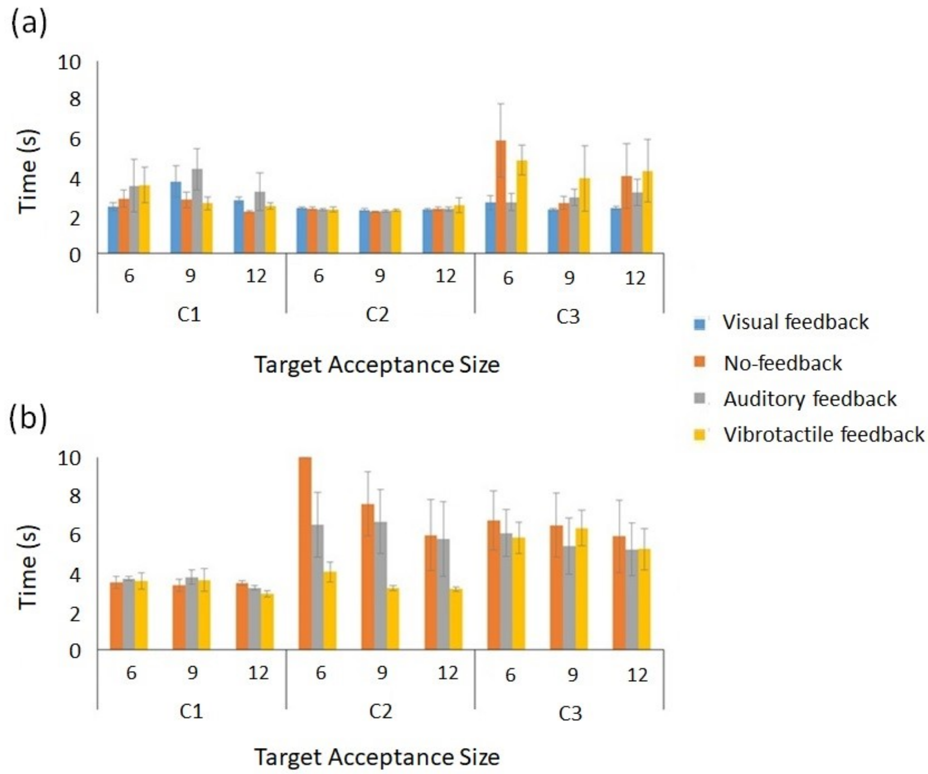

Figure 3- 8 The target selection time with the different target acceptance sizes and feedback modalities for the three child participants without impairments for (a) the on-screen experiment, and (b) the off-screen experiment

Child Participant with Physical Impairments

Figure 3-9 (a) and Figure 3-9 (b) indicate the target selection time for the on- and off-screen conditions of the child participant who had a physical impairment, D1. Visually inspecting the graphs shows that no-feedback appears to have the longest target selection time in all the target size and all the screen conditions. The auditory feedback had the shortest selection times for the on-screen condition, but vibrotactile feedback had the shortest times for the off-screen condition. The target selection time increases as the target acceptance size gets smaller in both screen conditions. In terms of the difference in the screen conditions, the average target selection time in the off-screen condition was 0.6% longer than in the on-screen condition. However, the average target selection time for the smallest target acceptance size was 9.1 % longer.

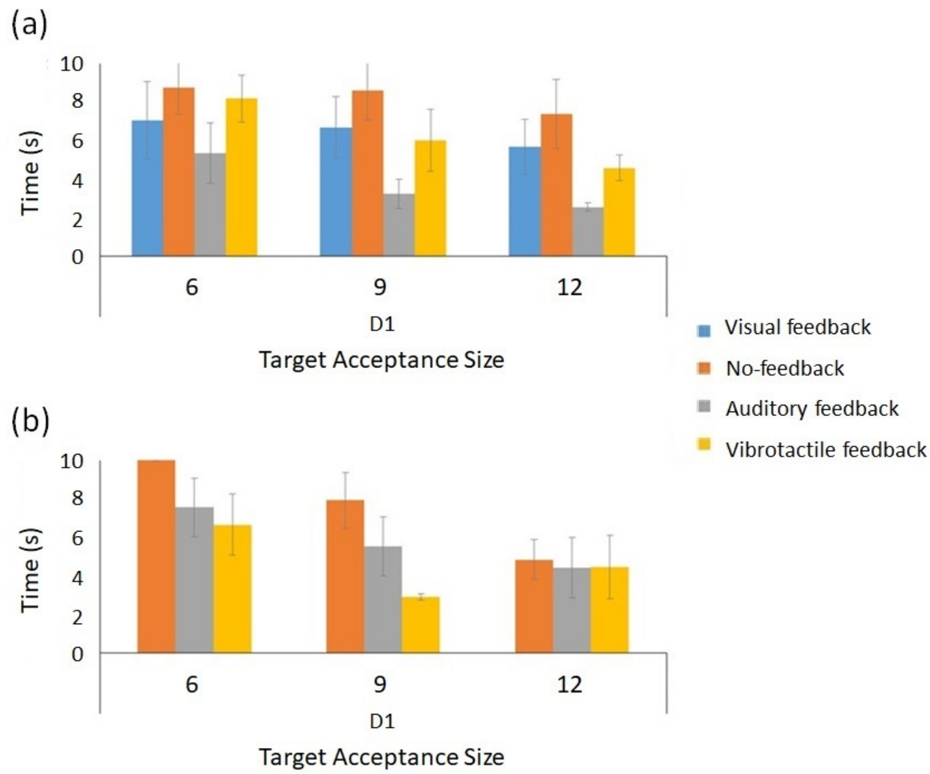

Figure 3- 9 The target selection time with the different target acceptance sizes and feedback modalities for the child participant with physical impairments. (a) is for the on-screen experiment, and (b) is for the off-screen experiment

3.3.2 Timeout Error Rate

The timeout error rate for each participant group in the screen conditions is shown in Table 3-1. The timeout error only occurred with the target acceptance size of S in both screen conditions for the adult participants without impairments. For the adult participants with physical impairments, a timeout error was rarely seen in all the conditions. The child participants without impairments performed well in the on-screen condition. Between 20 to 46% of timeout error rates were observed in the off-screen condition. The highest timeout error rate among all the participants occurred for the child participant with physical impairment, D1. The table also indicates that the no-feedback modality had the highest timeout error rates in both screen conditions. The auditory feedback had the lowest time out rate in the on-screen condition, and the vibrotactile feedback had the lowest time out rate in the off-screen condition, overall. In general, the time out error rate in the off-screen condition was higher than the on-screen condition for all the participant groups, though this was not statistically tested.

Table 3- 1 Time-out error rate (%) for the different target acceptance size and feedback modality in each population group for on-screen and off-screen experiment. (n=10 for the adults without impairments, n=2 for the adults with physical impairment, n=3 for the children without impairments, and n=1 for the child with physical impairment)

On-screen experiment					
	Size	Visual feedback	No-feedback	Auditory feedback	Vibrotactile feedback
Adult participants without impairments	3	3.3	12.1	8.5	10.2
	6	0.0	0.0	0.0	0.0
	9	0.0	0.0	0.0	0.0
Adult participants with physical impairments	6	11.1	0.0	0.0	0.0
	9	0.0	0.0	0.0	0.0
	12	0.0	0.0	0.0	0.0
Child participants without impairments	6	0.0	14.3	0.0	0.0
	9	0.0	0.0	0.0	6.7
	12	0.0	7.2	0.0	7.1
Child participant with physical impairments	6	60.0	80.0	20.0	40.0
	9	20.0	80.0	0.0	20.0
	12	20.0	60.0	0.0	0.0

Off-screen experiment				
	Size	No-feedback	Auditory feedback	Vibrotactile feedback
Adult participants without impairments	3	37.9	35.0	37.9
	6	0.0	0.0	0.0
	9	0.0	0.0	0.0
Adult participants with physical impairments	6	11.1	0.0	0.0
	9	0.0	0.0	0.0
	12	0.0	0.0	0.0
Child participants without impairments	6	46.7	20.0	0.0
	9	38.5	20.0	0.0
	12	26.7	20.0	0.0
Child participant with physical impairments	6	100.0	40.0	40.0
	9	60.0	20.0	0.0
	12	0.0	20.0	0.0

3.3.3 Questionnaire

Table 3-2 shows the preference among the feedback modalities for all the participants. For the adult participants without impairments, visual feedback was the preferred modality for the on-screen condition, and auditory feedback was the preferred modality for the off-screen condition. The no-feedback condition stands out as the least preferred feedback modality for all the screen conditions. The preferred feedback modality for the other participants was distributed quite evenly for the on-screen condition. However, in the off-screen condition, the most preferred modality was the auditory feedback. No-feedback was the least preferred feedback modality of all the participants for both conditions, except C1 and C3 for the on-screen.

The participants who preferred the visual feedback commented that the visual feedback was most intuitive because they could easily see where their gaze was being tracked by the system. However, C1 and C3 who chose the visual feedback as the least preferred feedback pointed out that the visual feedback was distracting when the location of pointer did not exactly match with the actual location of their gaze. The participants who ranked either the auditory feedback or the vibrotactile feedback as the most preferred modality liked how they knew how long to fixate their gaze on the target based on the intensity of the feedback provided. Another participant commented that the auditory and vibrotactile feedback modalities were intuitive but might take more time to get used to. Also, some participants commented that they preferred the auditory over the vibrotactile feedback because they liked the ramp-up sound that was given during the gaze fixation because it was more noticeable than the ramp-up vibration. One participant commented that an advantage of those feedback modalities was less eyestrain compared with the visual feedback.

Table 3- 2 The preferences of the participants for the feedback modalities in the on- and off-screen conditions. (n=10 for the adult participants without impairments)

	Most Prefered feedback modality		Least prefered feedback modality	
	On-screen	Off-screen	On-screen	Off-scree
A1-A10	Visual (4/10)	Auditory (6/10)	No-feedback (8/10)	No-feedback (9/10)
B1	Visual	Auditory	No-feedback	No-feedback
B2	Visual	Auditory	No-feedback	No-feedback
C1	Auditory	Vibrotactile	Visual	No-feedback
C2	Auditory	Auditory	No-feedback	No-feedback
C3	Vibrotactile	Auditory	Visual	No-feedback
D1	Vibrotactile	Vibrotactile	No-feedback	No-feedback

3.4 Discussion

Overall, the participants without impairments were statistically slower and less successful selecting targets in off-screen interactions with the physical environment than in on-screen interactions. The smaller the target acceptance size, the slower the participant to complete the target selection task in both the on- and off-screen conditions. The tasks performed with gaze fixation feedback modalities were accomplished statistically faster and more accurately than tasks performed without feedback, and similar results were observed in both screen conditions. However, the choice for which feedback modality to use going forward might be the user's preference. From visual inspection of the data of the participants with physical impairments, we saw that some of them had difficulty performing the eye gaze in the tasks, this was because they could not keep their head position still during the gaze interaction. But, providing feedback and increasing the target acceptance size appeared to help them to improve speed of the gaze interaction task.

The longer target selection time and higher timeout rate in the off-screen condition is likely because the targets in the off-screen condition were placed on the surface in a horizontal plane. A small difference of gaze movement in a vertical angle affected the accuracy of the gaze interaction with the task environment, especially for gazing at the target that was far from the participant. However, the timeout rarely happened with the larger target acceptance sizes in the on-screen as well as the off-screen condition if any feedback was provided.

Statistically significant differences in the target selection time were found only in the 3cm target acceptance size in both on- and off-screen conditions for the adults without impairments.

Interestingly, even though the target selection time in the smallest target acceptance size was quite different from the other two larger target acceptance sizes, performance with these two larger sizes was nearly the same. This is probably because the target selection time only increased when the degree of task difficulty exceeded what the user could handle.

The post hoc test revealed that the selection time in the no-feedback condition was significantly longer than the other feedback modalities. Thus, any feedback provided to the participants helped them to perform the most difficult target selection task. No significant difference between the audio, the vibrotactile, and the visual feedback was found in either the on or off-screen conditions. Therefore, the three feedback modalities were similar in their effectiveness. Regarding the timeout error with respect to each feedback modality, no-feedback had the highest error rate in both screen conditions, while the auditory feedback was lowest in the on-screen condition, and vibrotactile feedback was lowest in the off-screen condition. Other researchers have also found that it was not possible to quantitatively identify a clear "optimal" feedback, like Jussi Rantala et al. (2017), who found that feedback improved user's performance in gaze interaction, but all the modalities generally performed equally.

Looking at the qualitative experience of the participants, according to the questionnaire, the visual feedback was the most preferred feedback in the on-screen condition, auditory feedback was the most preferred feedback in the off-screen condition, and the no-feedback condition was the least preferred among all the feedback modalities. Even though the visual feedback was most often ranked as the best for the on-screen condition in adults, two child participants ranked it as the least preferred feedback. The problem with the disparity between the location of the gaze-based mouse pointer and the location they were gazing probably lowered their preference, whereas the disparity didn't seem to affect the preference for the adults. This type of disparity is one of the common issues for on-screen gaze applications (Zhang & Hornof, 2011). The comments about preferring the auditory over the vibrotactile feedback because auditory had the distinct ramp-up sound could be addressed for the vibrotactile feedback. The vibration amplitude is adjustable, so if the vibration amplitude was larger, more participants might have ranked it higher. Even though it was not most preferred, six out of sixteen participants did prefer it in the off-screen condition, and it could still have potential. As found in the review of Burke et al. (2006) visual-auditory feedback was most effective when a single task is being performed under normal workload conditions, which was the case in this study, but visual-haptic feedback was more effective for multiple tasks requiring high workload conditions, which would be the case when selecting targets to control a robot in future studies. Overall, the auditory feedback or the vibrotactile feedback could be suitable for the gaze interaction in off-screen scenarios, but it may generally depend on an individual preference.

3.5 Conclusion

This study demonstrated that the gaze interaction in an off-screen condition could be performed with a stationary eye tracker using the homogeneous transformation technique. The participants required more time to interact and select the target object in the physical environment than the target in the on-screen condition. The participant's performance in the target selection tasks varied depending on the age and the impairment with selection time generally being slower for younger children and physically impaired participants. However, they performed the target selection tasks in both conditions comparatively accurately and quickly if the size of the target was not too small for the participants to sustain their gaze on it. The results of the ten adult participants without impairments indicated that providing feedback to inform where gaze is fixated could make the gaze interaction performance statistically faster and more accurate in both screen conditions. However, none of the feedback modalities emerged as performing better than the others. With future development, this eye gaze system and feedback modalities will be integrated with an assistive robot platform, and used for play activities in the real physical world. This will contribute towards the goal of enabling children with physical impairment opportunities to perform object manipulation and interaction with objects in the physical environment.

Chapter 4

Implementation of Eye Gaze with Biofeedback in a Human-Robot Interface

4.1 Introduction

The way in which children develop their skills of cognition and perception is highly dependent on exploring objects and exploring their physical surroundings (Gibson, 1988; Musselwhite, 1986). When we refer to a child's cognitive development, we are referring to the ways they learn, feel, think, resolve problems, and know the environment (Bjorklund, 2005). Exploration of the environment through manipulating objects often occurs through play, which is essential to children's development (Besio, Dini, & Robins, 2007). When playing, a child receives information through sensory perception that helps them to become aware of the relationship they have with objects and other people surrounding them (Missiuna & Pollock, 1991). Playing helps the child to develop motor, social, cognitive, and language skills and helps them to learn, adapt, discover, master, create, and self-express (Ferland, 2003).

A child who has physical impairment may encounter problems with reaching, grasping, and moving objects during play, which can result in developmental delays across different areas (Robins et al., 2012). If children cannot demonstrate their skills through independent play, they may be perceived as having a greater degree of cognitive impairment than in fact exists, (Harkness & Bundy, 2001). Children with physical impairment frequently end up watching play instead of joining in, as others will frequently handle the play objects on their behalf (Blanche, 2008).

Children with physical impairment may be able to manipulate play objects by using robots such as the Lego robot (Rios, 2014) or the Play-ROB (Gernot Kronreif et al., 2007). These robots were controlled by multiple single switches in the case of the Lego robot and by a joystick in the case of the Play-ROB. Research has shown that such control mechanisms can be successfully used with such robots, with joysticks being the most intuitive (Harwin et al., 1988; Gernot Kronreif et al., 2007; Rios, 2014). However, children who have severe physical impairments may not be physically able to manipulate such interfaces.

Kinesthetic or other types of guidance through the user interface might help children to achieve control of the robot in spite of their disability. In a study by Atashzar et al. (2015), a haptics-enabled human-robot platform was controlled in a teleoperational mode, where an adult with disabilities operated a user interface (similar to a joystick) that controlled a task-side robot to perform object manipulation. One feature of the haptic capabilities of the system was to allow forces occurring at the task-side robot to be felt at the user interface, which is important because it allows children to perceive properties of objects. Interestingly, haptics can also be used to provide guidance to the user in order to better control the robot. A haptic system can limit the user's hand motion into a defined region using a so-called Forbidden Region Virtual Fixture (FRVF), so that the interface can help the users traverse the non-forbidden regions of the environment more efficiently (Abbott et al., 2007).

In one study, a computer vision system was used for defining appropriate locations of the FRVF based on visual information about the task environment, so the users could rely on the FRVF while they sorted objects into target destinations (Sakamaki, Adams, Gomez, et al., 2017). In a study of ten participants without impairments and one participant with physical impairments, the system successfully restricted the users' hand movement to a defined region during robot operation in a sorting task. The FRVFs were generated by a computer vision system, which did not allow the user to make mistakes. Thus, this system is not suitable to be used for situations such as games to compete for a score or assessments to test skill levels, which require measuring user's task errors.

The use of signals to indicate the user's intention can address this issue. Detection of eye gaze fixation is commonly used for selecting an object of interest on a graphical computer interface. It is easier to set up than other access methods that can detect user intention, such as brain-computer interface methods, and has less influence from environmental noises (e.g., power line noise or electromagnetic noise), and requires almost no training.

In general, visual feedback, such as a mouse pointer on a screen, is used to help the user to sustain eye movement on a target, because it informs the user how the system is interpreting the gaze. One of the technical difficulties of the gaze interaction application is to distinguish between spontaneous eye movements for gathering visual information and intentional eye movements for explicit selection, which is known as the Midas' touch problem (Møllenbach et al., 2013). In order to avoid unintentional selection, gaze fixation at the target of interest is needed for a prolonged period of time (the so-called dwell time). However, for a gaze interaction application that does not involve a display such as a target selection in the real-world, visual feedback like projected light, would make the system more complex. Auditory or vibrotactile feedback has been utilized for guidance of robot control (Rossa, Fong, Usmani, Sloboda, & Tavakoli, 2016). Those feedback modalities could be alternatives to visual feedback for gaze interaction.

In this study, auditory and vibrotactile feedback modalities for confirming target selection were implemented with a haptics-enabled robotic platform. With the implementation, the system allowed the user to select the target of interest in the physical environment by fixating their gaze on it, which in turn activated the FRVF guidance that assisted the user's robot trajectory towards the chosen target. A card sorting task using the system was performed by adults and children with and without physical impairments, and the task performance was examined to see if the feedback and guidance was helpful in completing the task. The research questions of this study were:

1. Can auditory feedback or vibrotactile feedback about gaze fixation location make target selection in the sorting task faster and more intuitive than without it?
2. Can the FRVF, determined by the gaze-based target selection, improve movement efficiency and ease of the robot operation compared to without it?

4.2 Methods

4.2.1 Participants

The research participants were ten adults without impairments (A1-A10), three males and seven females aged from 22 to 38 years (26 ±4.1); a 10 year, 2 month old boy without impairments (C1); and a 6 year, 10 month old girl without impairments (C2). The system was also tested with a 52-year-old female with quadriplegic cerebral palsy (AD1) and a 7 year, 4 month-old boy with right side spastic hemiplegic cerebral palsy (CD1). Participant AD1 had great difficulty handling objects and has been classified as level IV in the Gross Motor Function Classification System Expanded and Revised (GMFCS-E&R) (Palisano, Rosenbaum, Bartlett, & Livingston, 2007) and level III in the Manual Ability Classification System (MACS) (Eliasson et al., 2006). AD1 was affected by strabismus and had difficulty focusing on objects with both eyes simultaneously.

Participant CD1 had difficulty in reaching out and taking hold of objects with the limb on his affected side. He was classified as level I in the GMFCS-E&R scale and level III in the MACS scale. CD1 has no visual impairment; however, he was diagnosed with attention-deficit hyperactivity disorder which may cause reduced gaze concentration (i.e., a greater spread of vertical and horizontal eye movements) (Munoz et al., 2003). Ethical approval was received from the local Health Research Ethics Board Health Panel at the University of Alberta.

4.2.2 Task

The participants were asked to perform a card sorting task by using the haptics-enabled robotic platform. The sorting task in this study was a variation of the dimensional change card-sorting (DCCS) task, which is used to measure self-control and executive functioning in a playful scheme and is suitable for use with children from 3 to 7 years old (Kloo & Perner, 2005; Zelazo, 2006). The standard procedure of the DCCS task is that participants are instructed to sort cards, which differ along dimensions (e.g., shape and colour). In the test cards are sorted by the participants one way (e.g., by colour) in one set of trials and then they are asked to switch to another way (e.g., by shape) in the next set of trials. In this study, the figures on the cards varied according to three attributes: colour (red, blue, or green), shape (circles, square, or stars), and number of figures (one, two, or three). The participants were administered cards, one at a time, at a pickup point in the task environment, as shown in Figure 4-1. They were instructed to sort the card according to one of the attributes, randomly generated, into one of three target destinations by using the haptic user interface to control the task-side robot.

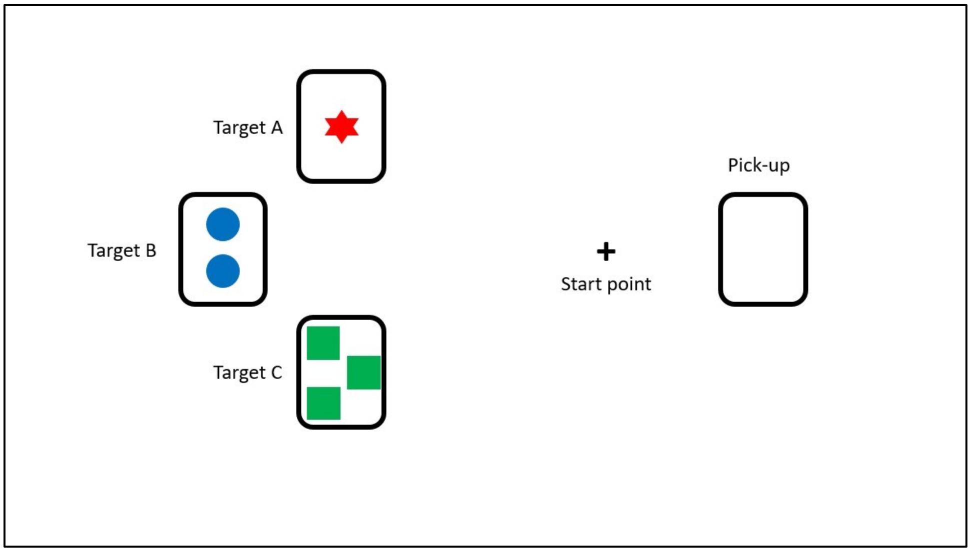

Figure 4- 1 Dimensional Change Card-Sorting (DCCS) set up. A pick-up point is located at the right side of the task environment. All the three-target point are located at the left side of the environment.

4.2.3 Experimental Setup

The system in this study consisted of two components: an eye gaze platform and a haptic robot platform as shown in Figure 4-2. Each component is described below.

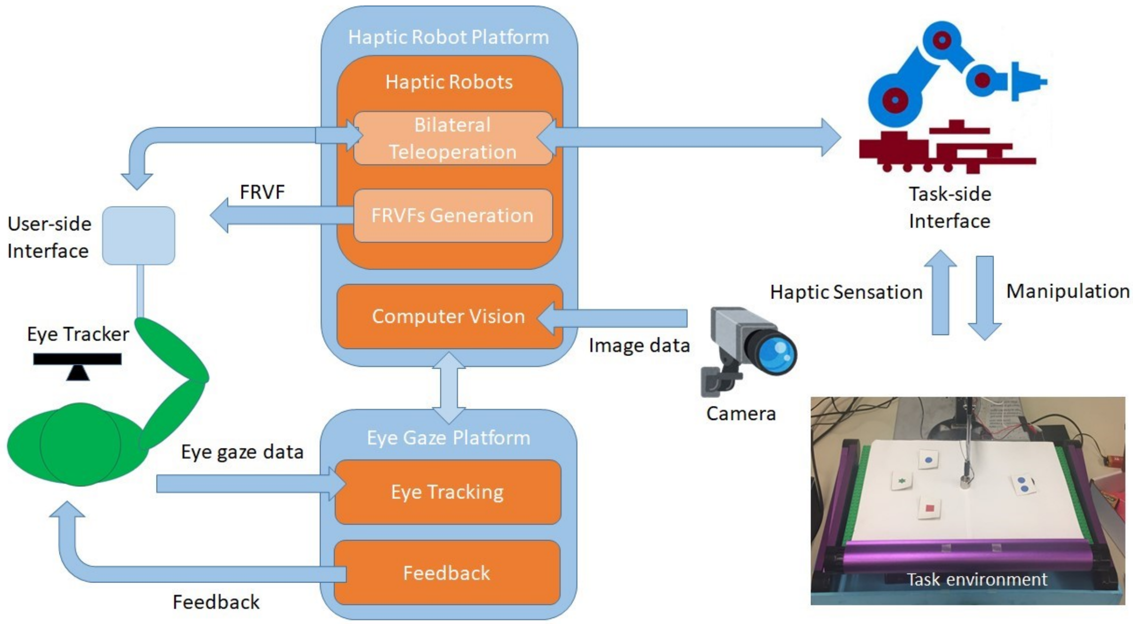

Figure 4- 2 Schematic diagram of the system in interaction with the user and the play environment

Eye Gaze Platform

The Tobii eye tracker 4C (Tobii Technology, Danderyd, Sweden) was used as an eye tracking interface. The eye tracker was placed 60 cm away from the participant and connected to a Windows PC in order to monitor fixation of the gaze during gaze interaction, with sampling frequency rate of 90Hz. The dwell time was set to 1.5 seconds to avoid unintentional selection. When the participant fixated their gaze on one of the three targets in the task environment for 1.5 seconds, the system recognized it as the target that the participant desired to select. If the participant’s gaze came off the target before 1.5 seconds was up and then came back on the target, counting of the dwell time started over again.

The eye gaze fixation feedback was given using a USB stereo sound adapter generating a 100 Hz sine wave output. For the auditory feedback, the sine wave was output as sound to earphones that the users wore, and for the vibrotactile feedback, the sine wave was sent to an amplifier to drive a vibration motor (Bit Trade One, Kanagawa, Japan). The motor was attached to the user interface, so that the motor was in contact with the participant's hand when they were holding the interface. The auditory or vibrotactile feedback (depending on the condition) began when the participant’s gaze was within a specified radius from the center point of the target. For the adult participants without impairments, the radius was set to 3 cm, and for the adult participant with physical impairments and all the child participants, the radius was set to 4.5 cm. This radius was chosen based on a pre-test to minimize the error of the target selection. The intensity of the feedback increased in proportion to the time the gaze was on the object, as an indication for the progression of the dwell time. The gaze acquisition and the feedback of the eye gaze platform was programed in LabVIEW (National Instruments, Austin, TX, USA). Gaze interaction with no feedback was also tested in the experiments (called no-feedback condition).

Haptics-enabled Robotic Platform

The haptics-enabled robotic platform consisted of two PHANTOM Premium 1.5A haptic devices (3D Systems, Inc., Rock Hill, SC, USA) programed to be operated synchronously in teleoperation mode (i.e., with a user-side haptic interface and a task-side robot). An electromagnet was attached on the tip of the task-side robot that could be switched ON or OFF, so that the participant could pick up a metallic card with it. The position of the end-effector of the task-side robot was controlled and monitored from a program coded in MATLAB/Simulink (MathWorks, Nadick, MA, USA) and Quarc (Quanser Inc., Markham, ON, Canada).

A USB webcam (Dynex, Richfield, MN, USA) was mounted over the task environment, which acquired the image data of the entire area of the environment. This image data was processed to obtain the position data of the targets and the card located in the task environment by using LabVIEW.

Homogeneous Transformations

Accurate position control of the haptic robots required the use of a homogeneous transformation that was calculated from three different separate position frames: the eye tracker frame, camera frame, and robot frame shown in Figure 4-3. The relationship between the position of the robot end-effector and a corresponding position of the eye gaze with respect to the fixed camera can be represented by a 4 x 4 homogeneous matrix *T*. This can be written as

$$^{C}P = {}^{C}_{E}T\,{}^{E}P \tag{4.1}$$

$$^{R}P = {}^{R}_{C}T\,{}^{C}P \tag{4.2}$$

where ${}^{E}P$ ${}^{C}P$, and ${}^{R}P$ denote three different augmented vector presentations of an arbitrarily chosen point represented in the eye tracker frame, camera frame, and robot frame, respectively. The ${}^{C}_{E}T$ and ${}^{R}_{C}T$ denote the transformation between the eye tracker and the camera frame, and the camera and the robot frame, respectively. Note that since the camera and the eye tracker could only acquire the points in 2-dimensional space, values on the y axis were set to a constant value that corresponded with the ground plane coordinates of the robot's position.

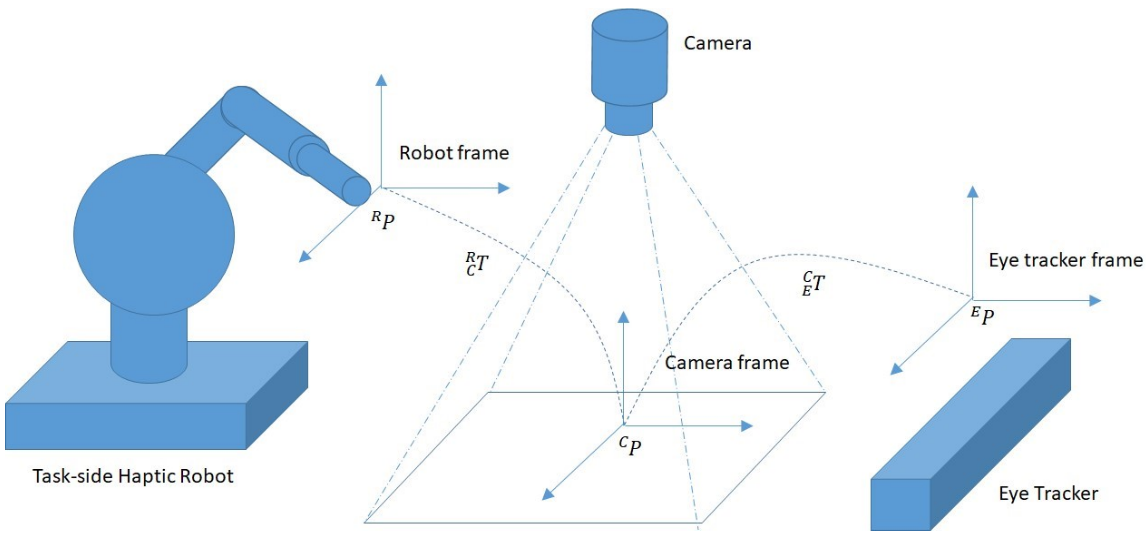

Figure 4- 3 Homogeneous transformations between point in the robot frame, the camera frame, and the eye tracker frame.

Forbidden Region Virtual Fixture (FRVF)

A FRVF was generated to restrict the robot end-effector within a desired region depending on the target destination. The FRVF was designed to be an ellipsoid shape generated between the pickup point of the card (preset to fixed x, y, and z coordinates) to one of three destination target points (preset to one of three x, y, and z sets of coordinates) determined by participant's gaze selection (See Figure 4-4). The ellipsoid-shaped FRVFs were obtained by rotating ellipses about the line joining the pickup point to the target destination point, and the parametric equations of an ellipsoid can be expressed as

$$P_{ellipsoid} = \begin{cases} x = a\cos\varphi\cos\theta \\ y = b\cos\varphi\sin\theta \\ z = \sin\varphi \end{cases} \tag{4.3}$$

for $\phi \in [0, 2\pi]$ and $\theta \in [0, \pi]$. Here, *a* and *b* are equatorial semimajor axes of the ellipse along the x-axis and y-axis, respectively. There was no force applied to the haptic end-effector inside the FRVF, but there were forces applied if the participant tried to move outside of the ellipsoid region.

The FRVF was implemented as a nonlinear spring attached between the current position of the robot's end-effector ($P_{end\ effector}$) and a reference point ($P_{reference}$) at each instant. The reference point was determined by the perpendicular projection of $P_{end\ effector}$ onto the z-axis of the ellipsoid. At each instant, the distance between $P_{end\ effector}$ and $P_{reference}$ was calculated and compared with the location of the surface of the ellipse. If the measured distance was greater than the surface, force (F_{VF}) was applied to the robot based on the following formula:

$$F_{VF} = \begin{cases} k * |distance|, & if\ distance > surface\ of\ the\ ellipse \\ 0 & ,\ else \end{cases} \tag{4.4}$$

$$where:\ k = spring\ constant, \qquad distance = P_{reference} - P_{end\ effector}$$

The spring constant determined the amount of force applied; the larger the *k* value, the stiffer the boundaries of the ellipsoid. The *k* value was set to 1 N/m. The forces were scaled up in a liner relationship so that the participant would feel a small force when coming into contact with the boundaries of the ellipsoid and a greater force if pushing further against the boundaries. The direction of F_{VF} was determined by the sign of the distance, i.e., toward the reference point in order to push the participant's movements away from the boundaries.

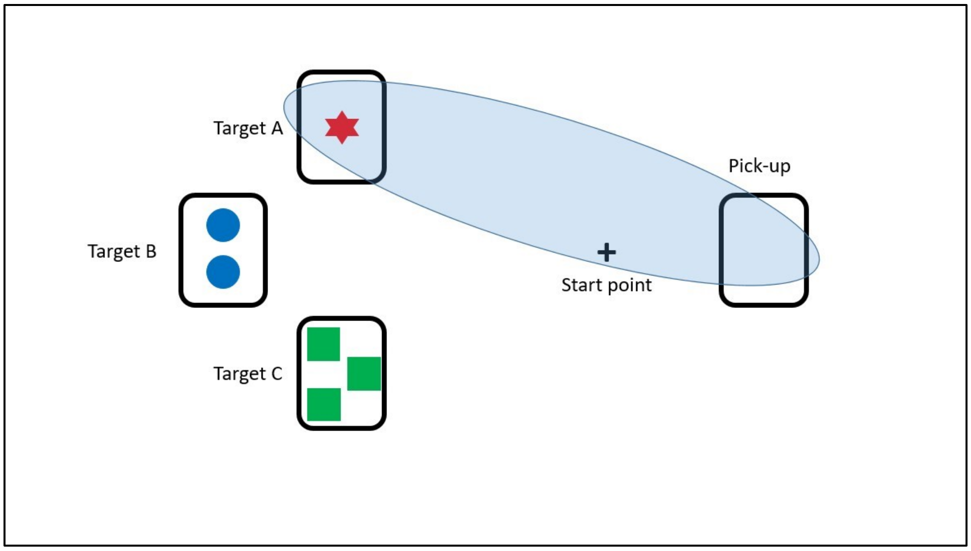

Figure 4- 4 The ellipsoid shaped FRVF placed between the pickup point and one of the target points in the task environment

4.2.4 Procedures

The task-side robot was placed behind the task environment, and the user interface was located beside the participant so they could easily reach it with the dominant hand. The position of the user interface was adjusted until the participant indicated they felt comfortable. Both the robot frame and the eye tracker frame were mapped to the camera frame of the task environment using the homogeneous transformation following a calibration procedure described below:

- A template on which four calibration points were printed was placed in the task environment.
- The participant sat in front of the task environment and fixated their gaze at each calibration point in turn. At the same time, the gaze position detected by the eye tracker at each calibration point was collected.
- The end-effector of the robot was placed on the calibration points by the researcher, and each position of the task-side robot was collected.
- The homogeneous transformation matrixes, as described above, were obtained from all the position data collected.

In the experiment, the researcher placed a card on the pick-up location and the participant was asked to sort the cards with the robots. The experimental protocol of the card sorting was the following:

1) The participant held the user interface with the dominant hand.
2) The system gave a verbal instruction to the participant about what attribute to sort on.
3) The participant fixated their gaze at the desired target destination. When the system determined that the participant's gaze was on a target, a voice confirmation was given to the participant (e.g., "target A was selected").
4) The participant moved the robot end-effector from the start point to the card pickup location shown in Figure 4-4.
5) When the robot end-effector reached the pickup point, the electromagnet attached on the tip was automatically activated, and the card was “picked up”.
6) The FRVF was activated towards the target point selected in step #3.
7) The participant moved the robot end effector along the FRVF to the target destination.
8) When the robot end-effector reached the target destination point, the card was automatically released from the interface.

The participant performed 12 trials of the card sorting in four different task conditions: FRVF-off with no feedback, FRVF-on with no feedback, FRVF-on with auditory feedback, and FRVF-on with vibrotactile feedback. The order of the task conditions was randomly assigned. The FRVF-off condition was used as a baseline of the participant’s task performance without any assistance from the FRVF. Thus, in the FRVF-off condition the participant did not have to select the target destination by gaze to activate the FRVF (i.e., steps #3 and #6 above were not performed).

4.2.5 Measurements and Analysis

The following variables were measured and analyzed for each trial:

- **Target Selection Time (measured in milliseconds):** The time from when the system gave the verbal instruction about what characteristic to sort on until the target was selected by eye gaze. A trial timed out and moved to the next trial if a participant could not select the target within 10 seconds.

- **Robot Travel Time (measured in milliseconds):** The time from when the card was picked up until it was released on the target destination.
- **Robot Trajectory Length (measured in millimeters):** The distance of the traveled path of the robot end-effector from the pickup point to the target destination point.

The **Correct Card Sorting Rate** was calculated for each task condition as the percentage of the number of cards that were sorted correctly divided by the total number of cards sorted in that condition.

At the end of the session, the participant ranked the feedback modalities according to their preferences. Also, the participant rated their agreement on a scale of one to five (1 = strongly disagree and 5 = strongly agree) on two statements regarding the system: (1) it was intuitive to use eye gaze to select a target, and (2) the tasks were easy to accomplish when the virtual fixture was used. In addition, the participants were asked if they had any comments to add.

Statistical analysis was conducted on the data from the ten adult participants without impairments (A1-A10). The Shapiro-Wilk normality test was performed first to check if the data was normally distributed. If the normal distribution of the data was confirmed, the target selection time was entered into an analysis of variance (ANOVA) with a factor of the feedback modality for the gaze fixation (3 levels: no-feedback, auditory feedback, and vibrotactile feedback). Additionally, the robot travel time, and the robot trajectory length were compared using an ANOVA with a factor of the task condition of the experiment (4 levels: FRVF-off, FRVF-on with no-feedback, FRVF-on with auditory feedback, and FRVF-on with vibrotactile feedback). In all cases, a probability of $p < 0.05$ was considered significant. If the data were not normally distributed, a pair-wise permutation test was used. Descriptive analyses of the data from the other participants were performed individually because of the heterogeneous sample. The **Percentage of Difference** for the target selection time, robot travel time, and robot trajectory length were calculated to express increase and decrease of the data from the baseline conditions (i.e., non-feedback condition for the target selection time, and the FRVF-off condition for the robot travel time and the robot trajectory length).

4.3 Results

4.3.1 Target Selection Time

A total of 36 trials (12 trials in each feedback modality) of the target selections were performed by each participant. The data of 6 trials from AD1 and 5 trials from CD1 were excluded due to the timeout error in target selection. Comparisons of the target selection time for the different feedback modalities are shown in Figure 4-5. No statistically significant difference between group means was found for the ten adult participants without impairments ($F[2,18]=0.23$, $p= 0.7927$).

Table 4-1 shows the percentage difference in the target selection time of the auditory and vibrotactile feedback from the no-feedback condition for the other participants.

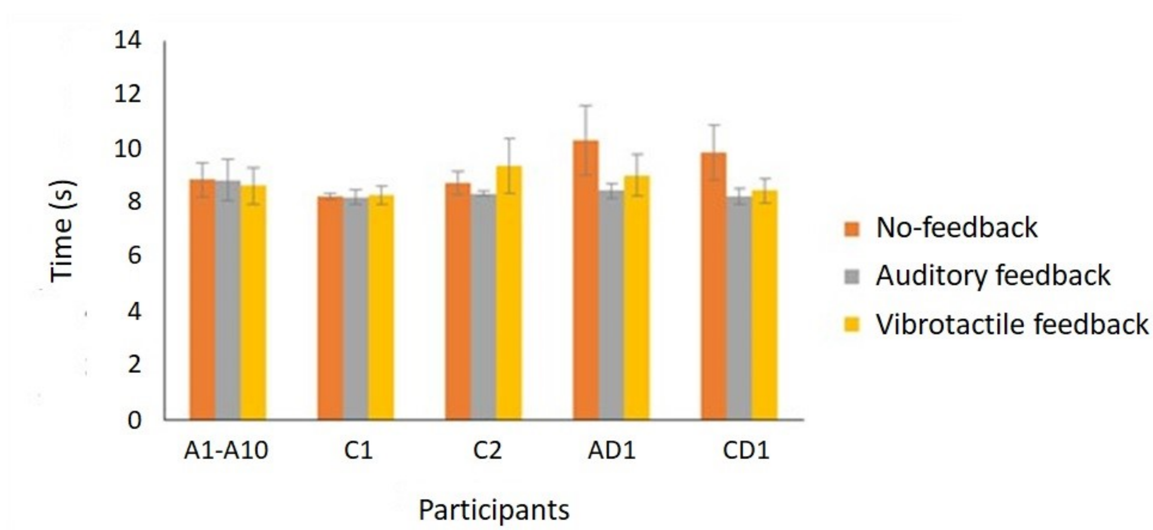

Figure 4- 5 Target selection time with the different feedback modalities for the ten adult participants without impairments (mean), and individual participants C1, C2, AD1, and CD1

Table 4- 1 Percent difference in the target selection time of the feedback modalities compared to the no-feedback condition for child participants and participants with disabilities

	Percent difference (%)	
	Auditory	**Vibrotactile**
C1	-0.3	0.71
C2	-4.51	7.04
AD1	-17.56	-12.55
CD1	-16.56	-14.4

4.3.2 Robot Travel Time

Figure 4-6 shows the average robot travel time of the 12 trials in each task condition for all the participants. From the figure, the time for the FRVF-off condition appears to be shorter than all the FRVF-on conditions for the ten adult participants without impairments, and performing the ANOVA for a statistical analysis, a significant difference was found ($F[3,27]=3.619$, $p= 0.0256$). The post hoc tukey's HSD test showed significant difference in the robot travel time between the FRVF-off and the FRVF-on with no-feedback condition.

Table 4-2 shows the percentage difference in the robot travel time of the FRVF-on conditions from the FRVF-off condition for the children without impairments and the child and adult with physical impairments.

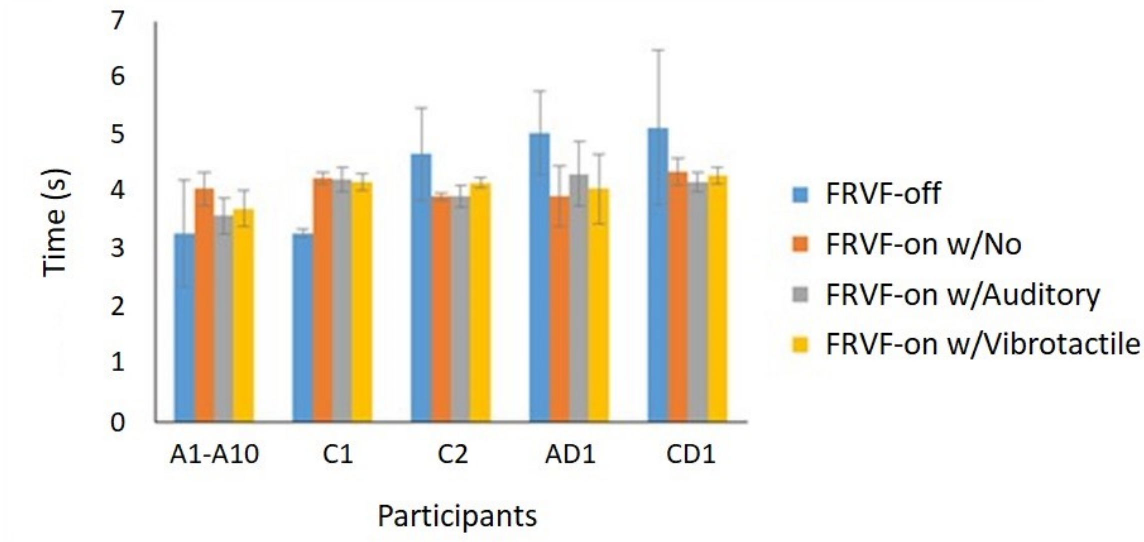

Figure 4- 6 Robot travel time with the different task conditions for the ten adult participants without impairments (mean), and the participants C1, C2, AD1, and CD1

Table 4- 2 Percentage of difference in the robot travel time of the FRVF-on conditions from the FRVF-off condition for the participants C1, C2, AD1, and CD1

	Percent difference (%)		
	FRVF-on (no-feedback)	**FRVF-on (Auditory)**	**FRVF-on (Vibrotactile)**
C1	29.48	29.18	27.66
C2	-15.78	-15.66	-10.75
AD1	-21.67	-14.06	-19.35
CD1	-15.05	-18.45	-16.33

4.3.3 Robot Trajectory Length

Figure 4-7 illustrates the robot trajectories during the entire task of each condition for a participant whose robot trajectory length was closest to the average among the adult participants without impairments and the participants C1, C2, AD1 and CD1. Figure 4-8 shows the average robot trajectory lengths for the 12 trials in each task condition. There was no significant difference in the robot trajectory length between the different task conditions for the ten adult participants without impairments (F=[3,27]=2.44, p= 0.0857).

Table 4-3 shows the percentage of difference between the FRVF-on conditions with the different feedback modalities and the FRVF-off condition.

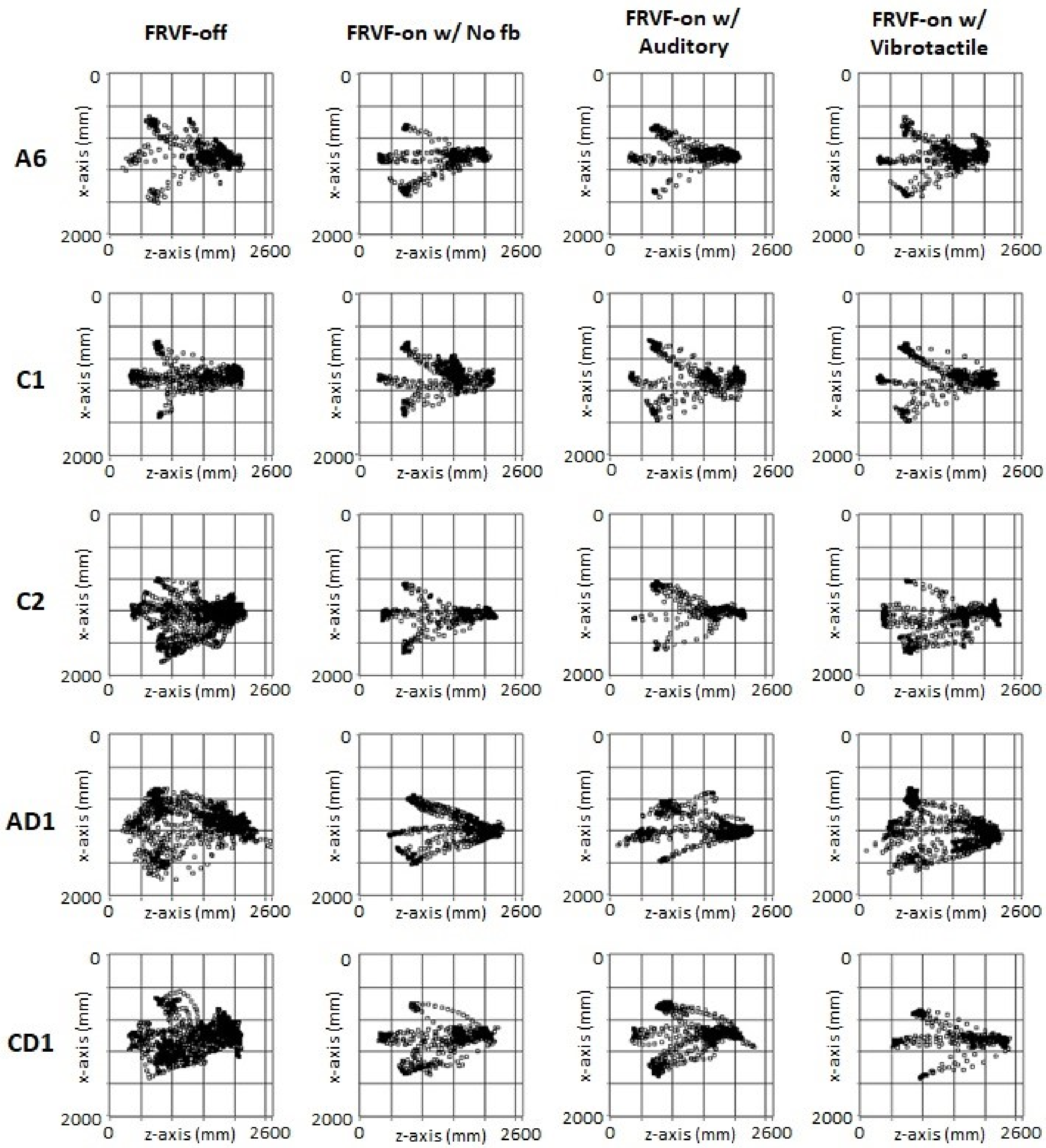

Figure 4- 7 Robot trajectories for one of the adult participants without impairments (A6), the participant C1, C2, AD1, and CD1 during: FVRVF-off, FRVF-on with no-feedback, FRVF-on with auditory feedback, and FRVF-on with vibrotactile feedback

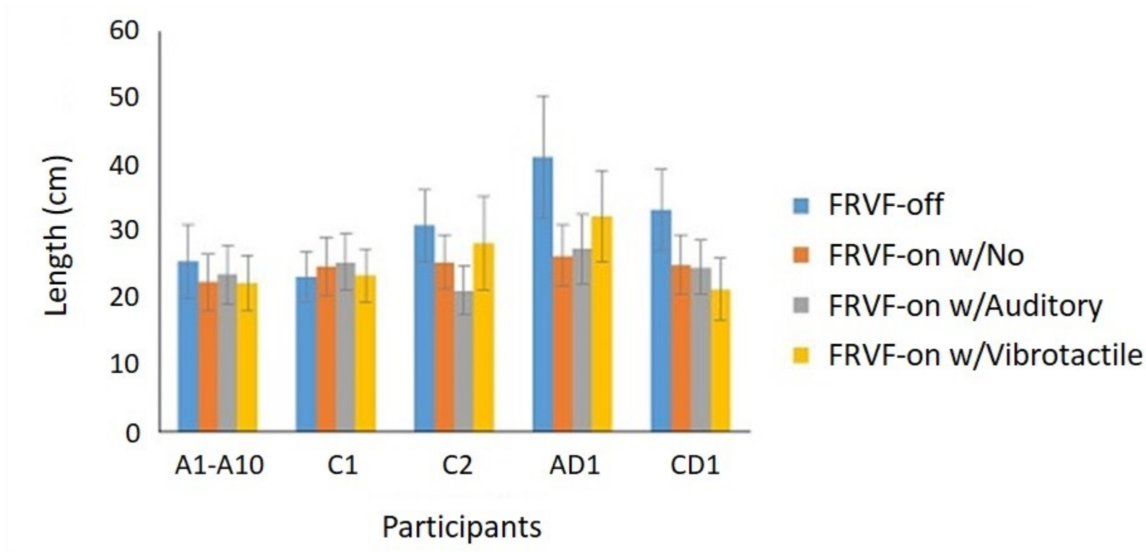

Figure 4- 8 Robot trajectory length with different task conditions for the ten adult participants without impairments (mean) and individual participants C1, C2, AD1, and CD1.

Table 4- 3 Percentage of difference in the robot trajectory length of the FRVF-on conditions from the FRVF-off condition for all the participants

	Percent difference (%)		
	FRVF-on (no-feedback)	FRVF-on (Auditory)	FRVF-on (Vibrotactile)
C1	6.63	9.67	1.33
C2	-17.52	-31.25	-8.23
AD1	-35.94	-33.47	-21.62
CD1	-24.65	-25.79	-35.56

4.3.4 Correct Card Sorting Rate

The correct card sorting rates for all the participants are summarized in Table 4-4. None of the ten adults without impairments made any mistakes in the card sorting in the experiments. Likewise, the adult participant with physical impairment AD1 and the child participant without impairments C1 made no mistakes. The child participants C2 and CD1, however, made some sorting mistakes during the runs with average correct card sorting rates of 67% and 70%, respectively.

Table 4- 4 Correct card sorting rate in the different task conditions for all the participants

	Correct Card Sorting Rate (%)				
	A1-A10	**C1**	**C2**	**AD1**	**CD1**
FRVF-off	100	100	91.67	100	75
FRVF-on w/ No-feedback	100	100	50	100	84.62
FRVF-on w/ Auditory	100	100	66.67	100	66.67
FRVF-on w/ Vibrotactile	100	100	58.33	100	54.55
Average	100	100	67	100	70

4.3.5 Questionnaire

Table 4-5 summarizes the preference of the feedback modalities and the responses to the questions regarding the intuitiveness of eye gaze for selecting targets and ease of use of the FRVFs for robot control. Seven out of ten adult participants without impairments indicated that the vibrotactile feedback was the most preferred feedback modality for the gaze fixation. Participants AD1, C1, and CD1 also preferred the vibrotactile feedback compared to the other feedback modalities, while C2 preferred the auditory feedback. Some participants commented that the vibrotactile feedback was preferred because the hand was already being used for operating the robot, so sensing the vibrotactile feedback at the interface was easier and more intuitive. Another participant commented that auditory feedback was sometimes distracting and made it more difficult to hear the task instructions.

For the questions about the intuitiveness of the gaze-based target selection, the modal score for the adults without impairments was 4 out of 5. However, one adult without impairments and the adult with physical impairments, AD1, rated intuitiveness as 3. They commented that they did not like to have to take the extra step of gazing at the target in order to perform the card sorting. The ease of use of the FRVF was rated at least 4 out of 5 by all the participants. The comments from most of the participants indicated that the FRVF helped them to accomplish the sorting task by giving the correct direction to move their hands, however, a few participants mentioned that the FRVF sometimes disturbed their desired movement path.

Table 4- 5 Preference of the feedback and responses to statements regarding the robot operation tasks (1 = strongly disagree, 5 = strongly agree)

		Most preferred feedback	Least preferred feedback	Intuitiveness of gaze-based target selection	Easier with FRVF
A1-A10	Range	NA	NA	3 to 5	4 to 5
	Mode	Vibrotactile (7/10)	No-feedback (10/10)	4	5
C1		Vibrotactile	No-feedback	5	5
C2		Auditory	No-feedback	4	4
AD1		Vibrotactile	No-feedback	3	4
CD1		Vibrotactile	No-feedback	5	5

4.4 Discussion

In this study, we developed a haptic robot platform which helps guide the user toward the desired target chosen with eye gaze fixation. Different feedback modalities were tested, but no statistically significant difference in target selection time was observed in the results of the adult participants without impairments. This is likely because the 3 cm acceptance size for the gaze fixation was large enough for them to easily select the target. Visual analysis of the data in Figure 4-5 and Table 4-1 indicated that the performance of the child participant without impairments C1 was similar to the results of the adults without impairments, having no difficulty performing gaze fixation even with no feedback. C1 was 10 years old, and appeared to have mature eye gaze behaviour, like adult participants. The target selection time for the 6 year-old child participant without impairments, C2, differed among the feedback modalities and visual analysis indicates that the time for the vibrotactile feedback was longer than the no-feedback condition. C2 had trouble following instructions to stay still during the tasks, and the system needed to be recalibrated many times during the experiments. This may have caused the inaccuracy in the gaze fixation. Visual analysis of the performance of the target selection for the adult participant with physical impairments, AD1, and the child participant with physical impairment, CD1, showed they performed similarly. The no-feedback modality took more time to select the target, meaning that the feedback must have been helping them sustain their gaze on the target. The difference in target selection time between auditory feedback and vibrotactile feedback appears to be smaller compared to the difference between the no-feedback and other feedback modalities. For adult participants without impairments, there were no significant differences in target selection time between auditory and vibrotactile feedback. Our findings are similar to findings of Jussi Rantala et al. (2017). He reported that feedback has been found to improve performance in gaze interaction, however, all the modalities generally perform equally.

Most participants reported that they preferred the vibrotactile feedback. Consistent with this preference, they often commented that the auditory feedback sometimes made it difficult to hear task instructions and the vibrotactile feedback was more intuitive. C2 preferred the auditory feedback, and that was the feedback modality with which she performed the fastest. However, some participants preferred the vibrotactile feedback even though it did not result in their fastest target selection time. Apparently, task performance was not the only criteria for determining preference of the feedback modalities; personal preferences must also be considered. However, the time differences between the auditory and the vibrotactile feedback modalities were generally around a few hundred milliseconds in each target selection, thus, the performance difference between the two feedback modalities may not have been clearly distinguishable for many participants.

For the performance of robot operation, a significant difference between the FRVF-on conditions and the FRVF-off condition was found for the adults without impairments, and the FRVF-on condition resulted in statistically longer travel times compared to the FRVF-off condition. This is contrary to our expectation, but likely caused because the participants tended to follow along the boundary of the FRVF and explore it when it was on, which was a detour from a straight line between the pickup point and the target point. The same tendency was also seen with the 10-year-old child participant without impairments, C1, during the trial. Visual analysis indicated that the difference in robot travel time for C1 was shorter when the FRVF was off, and one can see that he was being very efficient in his robot trajectories when the FRVF was off (See Figure 4-7). On the other hand, the FRVF appears to have made the travel time shorter for the adult participant with physical impairment, AD1, the child participant with physical impairment, CD1, and the 6-year-old child participant without impairments C2. These results suggest that the FRVF was not required for participants without impairments to have efficient robot trajectories, since the FRVF actually behaved opposite to what we would expect, but the participants with physical impairment and the youngest child participant did benefit somewhat from the FRVF as far as time of the robot trajectory.

The robot trajectory length with FRVF-off was expected to be longer than the FRVF-on conditions because for the latter, the participant's trajectory is constricted to prevent unnecessary robot travel. However, no significant difference was found for trajectory length in the results of the adult participants without impairments. From Table 4-3, the robot trajectory lengths of AD1 and CD1 with the FRVF-off condition were more than 20% longer than the FRVF-on conditions. Visually inspecting the figures of the robot trajectories in Figure 4-7, the trajectory path was more spread out during the task with FRVF-off than in the FRVF-on conditions for participants AD1 and CD1 compared with the trajectory of the average adult without impairments. The results of the 10 year-old child participant without impairments, C1, appeared to be similar to the results of the adults without impairments. He had well developed motor skills to perform the robot operations. The trajectory of the 6 year-old child participant without impairments C2 appears to be more spread out, likely because she had less motor skill than the adult participants without impairments.

Most participants rated the ease of the robot operation with the guidance of the FRVF at least 4 out of 5 on the questionnaire. The participants felt that the FRVF helped them to accomplish the tasks. The ratings of the adults without impairments and C1 indicated that the task was easier with the FRVF for them even though robot travel time was shorter and trajectory length was longer. It is interesting that they still felt that the FRVF was helpful even though it did not improve their task performance.

The variation of the DCCS task was used in this study in order to have a task where the participants could make mistakes. The task should have been quite easy for most of the participants since they had the cognitive skills to understand the concept of object classification. Therefore, the 100% correct card sorting rate achieved by the adult participants without impairments and the adult participant with physical impairments, AD1, is expected. Zelazo (2006) stated that the DCCS task was designed to assess executive function and suitable for use with children under 7 years old. Even though the modified version of the DCCS used in this study required participants to sort on a new dimension for each card in a set of trials (unlike the standard DCCS where individuals sort cards according to one dimension for each set of trials), the 100% correct rate made by the 10 year-old child participant without impairments, C1, was also expected. The 6 year-old child participant without impairments C2 and the 7 year-old child participant with physical impairments, CD1, are still in the skill acquisition phase, thus their lower performance is also expected. It is worth mentioning that C2 achieved 91.67% correct card sorting rate in the FRVF-off condition, but the correct card sorting rates decreased to 50-66% in the FRVF-on conditions. A potential reason was that fixating her gaze on the target point to generate the FRVF before doing the card sorting may have increased the task complexity and affected her performance.

This study had some limitations yet to be mentioned. First, due to the small sample size of the participants with physical impairments, the findings in this study can serve only as preliminary data to guide further research. Second, there were timeout errors in 16.6% and 13.9% of the trials for the adult and the child with physical impairment, respectively. This means that they were not always able to sustain their gaze within the radius of 4.5 cm on the target location for the full 1.5 second dwell time to complete the selection before the timeout occurred (10 second timeout window). Their impairments, specifically the spasticity and strabismus for AD1 and the attention-deficit hyperactivity disorder for CD1, may have made it difficult for them to accurately fixate their gaze for target selection. Increasing the acceptance size could help make the target selection easier; however, this would result in fewer targets allowed in the environment. Instead of simply increasing the target acceptance size, applying machine learning techniques for the system to adapt to each individual's gaze behaviour could improve the success rate of the target selection for these populations. Third, a stationary eye tracker was used to capture the eye movements and map the gaze to the physical environment. In general, a stationary eye tracker is lower cost, however, but it may not be very for situations where the users are not able to stay still and fixate the head position within the range of the gaze detection. Replacing the stationary eye tracker with a head-mounted eye tracker would help attain stable gaze acquisition and give more freedom for users to perform the gaze interaction naturally during the tasks, as long as the users could tolerate wearing one. Lastly, the FRVF limited the range of user’s movement within a defined region, however, it did not provide a guidance force toward the target destination. With future development, guidance VFs could be added where the system detects the intended destination of the user and assists the user in moving the robot to the intended destination.

4.5 Conclusion

The main contribution of this study was that if the users made a mistake on the card sorting task, the system was able to create a FRVF towards the target point the users chose by eye gaze fixation. This is an improvement over the system in Sakamaki, Adams, Gomez, et al. (2017), where the FRVF was created based on object recognition of the task environment by computer vision and the system never allowed the users to make mistakes. The system developed in this study can be used for situations such as games with scores or assessments to test cognitive skill levels where users may make mistakes. The results of the study indicate that feedback for the gaze fixation plays an important role helping users to select the target in the environment, especially for people who have difficulty with the gaze fixation. Also, the FRVF was able to restrict a user's hand movement inside a defined region to improve the efficiency of the movement for an adult and a child with physical impairment to perform the card sorting task. From this perspective, the system allows the users with physical impairments to have more efficiency interacting with the physical environment. The system improvements made in this study can be useful and beneficial for the development of the system, and further development can support children's participation in play activities.

Chapter 5

Effectiveness of Haptic Feedback for Brain-Computer Interface Training

5.1 Introduction

Play represents a critical activity by which children explore their environment by manipulating objects within it (Besio et al., 2007). During play-based experiences, children's awareness of the objects and people that exist within the environment increases (Missiuna & Pollock, 1991). Play can make a positive contribution to a child's development of motor, social, linguistic, and cognitive skills, and it also stimulates creativity, learning, mastery, self-expression, and adaption (Ferland, 2003).

Children who have physical disabilities may find it difficult to participate in certain play-based activities as a result of impairments that affect movement, grasping, and reaching out for objects. This can impede their development across multiple areas (Robins et al., 2012). In some cases, the difficulties children encounter can lead to the perception that they are more developmentally delayed than they actually are because they are unable to demonstrate their full capabilities through independent play (Harkness & Bundy, 2001). Furthermore, children who have some form of physical impairment tend to watch others playing rather than participating themselves because their playmates more effectively or frequently handle the play objects (Blanche, 2008).

Robots, such as Lego robots (Rios, 2014) and the Play-ROB (Gernot Kronreif et al., 2007), have helped children who have physical impairments to play with objects. Interfaces such as a joystick for the Play-ROB (Gernot Kronreif et al., 2007) and switches for the Lego robots (Rios, 2014) can help children with impairments to control robots. However, the extent to which this is possible can vary according to the extent of the child's physical impairment, and may not be useable by children who have significant physical impairments.

Recently, brain-controlled access pathways, often referred to as brain-computer interfaces (BCI), have been proposed as a new means of biological signals-based device control (McFarland & Wolpaw, 2011). BCI can translate an individual's brain activity to use computer applications, and control devices such as robots or neuroprostheses (Collinger et al., 2013). Electroencephalography (EEG) is a non-invasive method to record the brain's activity and can be detected by electrodes placed on the surface of the scalp (Nunez & Srinivasan, 2006). The brain response associated with real or imagined movement produces reliable changes in the sensorimotor rhythms of the EEG. Sensory processing of real or imagined movement shows a decrease of spectral amplitudes of alpha rhythm in the range from 8 to 13 Hz, as originally reported by Berger (1931). This decrease in oscillatory activity is known as Event-Related Desynchronization (ERD) (Pfurtscheller & Aranibar, 1979). The opposite, namely the increase of spectral amplitudes of beta rhythm in the range from 13 to 26 Hz, is termed Event-Related Synchronization (ERS) (Pfurtscheller & Neuper, 2010). Thus, brain patterns can be detected, processed, and classified as performing motor imagery or resting, which can be used as commands to control technology.

Several BCI research studies using ERD/ERS have involved participants with and without physical impairments, and in some studies they controlled technology with the signals (Cincotti et al., 2008; Daly et al., 2014; López-Larraz, Montesano, Gil-Agudo, & Minguez, 2014). These studies indicate that ERD/ERS is potentially a feasible channel for BCI applications for people with neurological impairments. For example, D. Huang, Lin, Fei, Chen, and Bai (2009) tested BCIs for 2-dimensional cursor control based on ERD during motor execution and motor imagery with 5 participants without impairments. Brain signals were detected and classified according to physical movement, motor imagery or rest using various machine learning methods. Linear Discriminant Analysis (LDA), Decision Tree, and Support Vector Machine (SVM) provided accuracy rates as high as 88% for the physical movements and 73% for the motor imagery. In Cincotti et al. (2008), 14 participants without impairments and 14 participants with spinal muscular atrophy or Duchenne muscular dystrophy successfully performed 2-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 López-Larraz, Montesano, Gil-Agudo, and Minguez (2014) evaluated the ERD/ERS of 6 participants without impairments and 3 participants with 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.

In these BCI studies, successful BCI classification accuracy was around 70% to 90%. The sensorimotor rhythm is often unstable, weak, and difficult to detect. Even with the best classification algorithms, classification accuracy of the motor imagery tasks depends on how well an individual can voluntarily modulate their neural activity. Tan and Nijholt (2010) estimated that between 15% and 30% of the non-disabled population cannot produce the ERD/ERS to control a BCI on their first session interacting with BCI. It is recommended that BCI control employ repeated practice with feedback and rewards, and also intensive training in order for the participants to acquire the skill to control the BCI system (Graimann, Allison, & Pfurtscheller, 2010).

One of the most widely used and successfully employed BCI training protocols in the field of BCI research is the Graz training protocol (Jeunet, Jahanpour, & Lotte, 2016). 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 they are imagining movement or resting. The user receives visual feedback on a computer screen in order to improve the strength of their ERD/ERS brain response (Graimann et al., 2010).

Our long-term goal is to enable children who have severe physical disabilities to use BCI to control a robot in a physical play environment. Instead of using visual representation of neurofeedback, which requires a visual display, other feedback methods will be needed. Haptic feedback has been trialled as biofeedback in BCI applications (Angulo-Sherman & Gutiérrez, 2014). Haptic feedback can be tactile or kinesthetic sensations: tactile sensation is normally conveyed through the skin, such as by pressure or vibrations, while kinesthetic sensation refers to static and dynamic posture based on muscles and tendons that allow us to feel the pose of our body (Sigrist et al., 2013). Angulo-Sherman and Gutiérrez (2014) studied the effects of vibrotactile feedback by comparing it with visual and auditory feedback in a motor imagery task with up to 7 runs of the BCI training. Researchers did not find a significant difference between the feedback modalities and concluded that BCI performance varies among participants. Passive movements can induce EEG patterns similar to those observed during motor imagery, so some studies have used kinesthetic feedback through a haptics-enabled robot to help induce sensorimotor rhythms

(K. K. Ang et al., 2011; Gomez-Rodriguez et al., 2010). Most BCI studies do only a single session, especially those focusing on system development. However, using kinesthetic haptic feedback over several sets of BCI training could yield benefits in terms of improving the strength of a user's ERD/ERS brain response.

In this paper, a BCI system and training protocol were designed that provided kinesthetic haptic feedback according to the detected movement intention. Classification accuracy was compared to visual feedback in sets of BCI training sessions with ten adults without impairments, reported in Study 1, and one adult with cerebral palsy and one child without impairments, reported in Study 2. The research questions of these studies were:

1. Which feedback modality (visual or kinesthetic 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 brain activity differ between a motor imagery task with visual feedback and haptic feedback?
4. Which feedback modality leads to a lower workload for the participants?

Study 1

5.2 Methods

5.2.1 Participants

Ten university students without physical disabilities, six males and four females, aged from 22 to 38 years (28 ±4.3), participated in the study. The participants were all right-handed and had no prior BCI experience. Ethical approval was received from the local Health Research Ethics Board Health Panel at the University of Alberta.

5.2.2 Experimental Setup

An EEG acquisition hardware device called OpenBCI (OpenBCI, Inc., Brooklyn, NY, USA), an open source BCI software called OpenViBE (Renard et al., 2010), 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 for kinesthetic haptic feedback. A picture of the system is shown in Figure 5-1, and a schematic diagram of the system is shown in Figure 5-2.

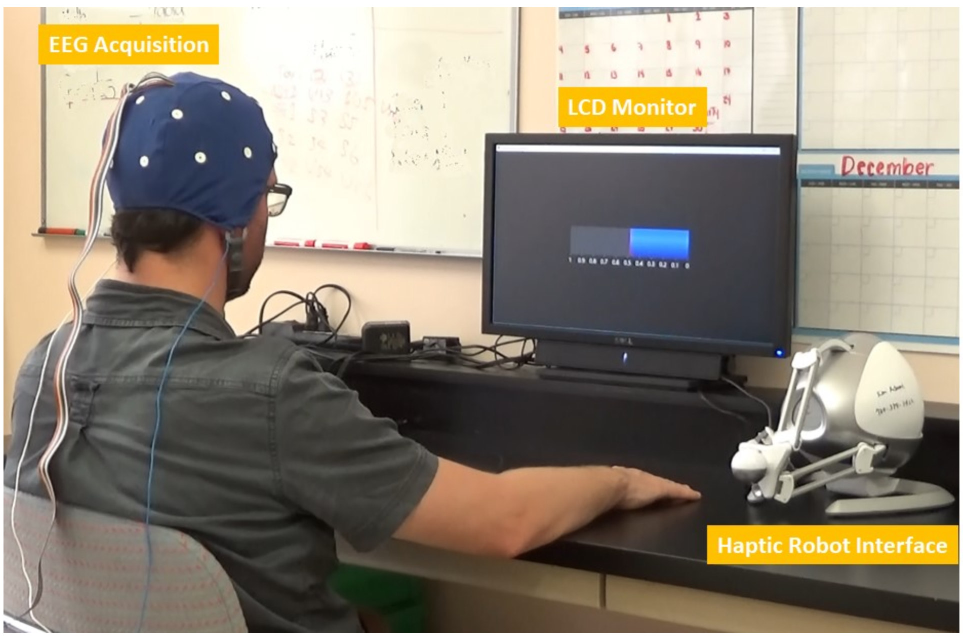

Figure 5- 1 Picture of the BCI training system

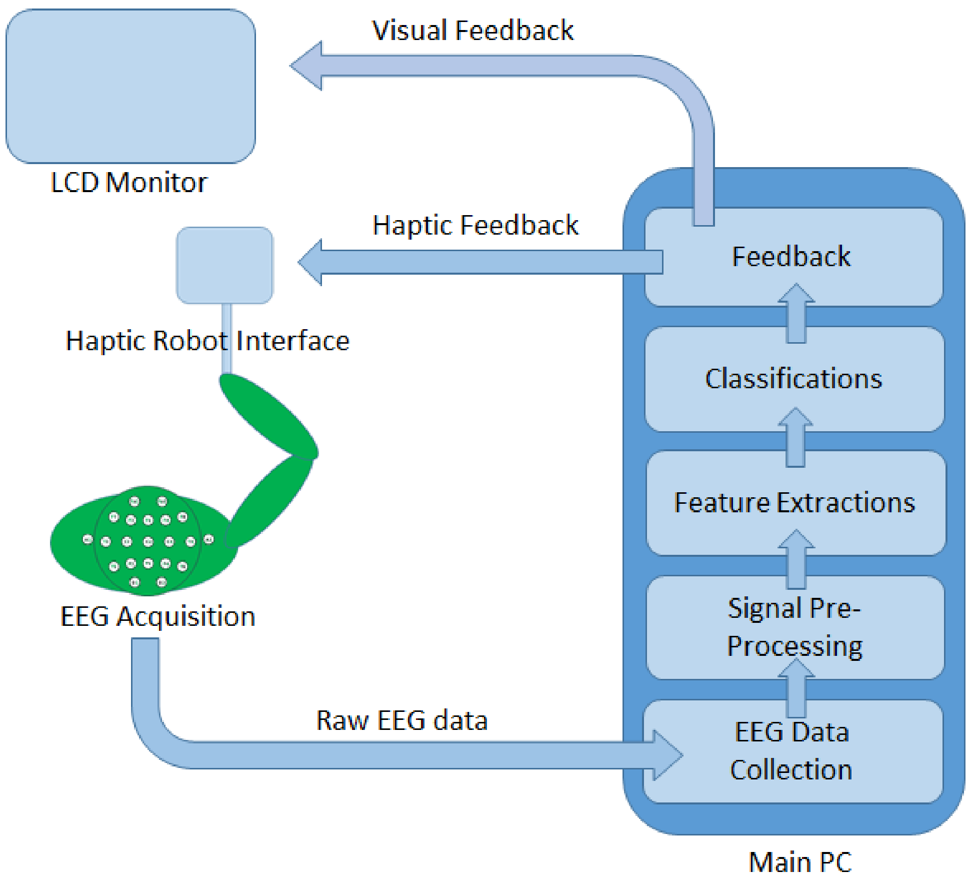

Figure5- 2 Schematic diagram of the BCI system

EEG Data Collection

The EEG was sampled with a 250 Hz sampling frequency, and an EEG cap with eight channel electrodes was placed on the surface of the participant's scalp to collect their EEG signals. Channels Cz, Cp, F3, C3, P3, F4, C4 and P4, according to the 10-20 international system, were selected since they are over the pre-motor 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. The OpenViBE only collected the EEG data while the participants were performing the BCI trials (i.e., motor imagery or rest) and excluded the data between the trials where the motor imagery tasks were not performed).

Signal Pre-processing

The collected EEG data was preprocessed in real-time through a notch filter with cut-off frequencies between 58 and 62 Hz to reject power line noise. Then, the signal was band-pass filtered from 7 to 30 Hz to ensure the alpha and beta frequency bands were passed.

Feature Extraction

In order to retrieve the component signal that best represents 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 (Pfurtscheller, Neuper, Guger, Harkam, Ramoser, Schlögl, et al., 2000). 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 (Koles, Lazar, & Zhou, 1990). The filtered signals were then split into blocks of 1 second every 0.0625 seconds and the logarithmic band powers were computed. The feature vector extract of the CSP filter and the logarithmic band power was then sent to the classification module.

Classification

Linear Discriminant Analysis (LDA) was used for the BCI classification (i.e., MOVE or REST) because in the study of Sakamaki, Campo, Wiebe, Tavakoli, and Adams (2017), LDA and linear Support Vector Machine (SVM) achieved better BCI classification accuracy than the Multilayer Perceptron (MLP) with participants without impairments, and in another study, LDA yielded better BCI classification accuracy compared to the SVM and MLP with participants without impairments (Romero-Laiseca, Sakamaki, Adams, Bastos-Filho, & Frizera, 2019). After the data was classified using the LDA, the control loop was closed with the feedback, which is explained in the next section.

Feedback

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 presented as a value in the range of [0, 1]. Smaller confidence values corresponded to the classification of REST while larger confidence values corresponded to the classification of MOVE.

Kinesthetic Haptic Feedback

Kinesthetic haptic feedback, i.e., passive movement of the participant's hand based on the sensorimotor rhythm brain response, was done 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 force the participant put on the haptic robot interface was measured to confirm that the participant was not physically pushing the end-effecter of the interface, but was just moving it by their motor imagery. If more than 4N of interaction force was detected from 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.

5.2.3 Procedures

Experiments

There were six sessions for each feedback modality. To prevent confounding with practice effects, the order of the feedback conditions was counterbalanced across the participants. 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. 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.

During the classifier training, 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 repeated 15 times in each BCI run. The sequence of the cue was as follows: 1) 5 seconds of a blank screen, 2) 2 seconds of a cross displayed on the screen, and 3) 6 seconds of the cue (either MOVE or REST) while the participant performed motor imagery about the task indicated by the cue. For visual feedback, the participant's arms rested on a table in front of them. For kinesthetic haptic feedback, the same sequence of the cue was used, but the participants held the end-effector of the haptic robot interface, and the kinesthetic haptic feedback was provided to the participants when the cue indicated 'MOVE'.

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 6 seconds of the cue, the cue was displayed for 1.25 seconds and then there were 8 seconds of feedback provided. For visual feedback, the bar indicator representing the confidence value was provided. For kinesthetic haptic feedback, the haptic interface guided the participant's hand from right to left according to the confidence value (see Figure 5-3).

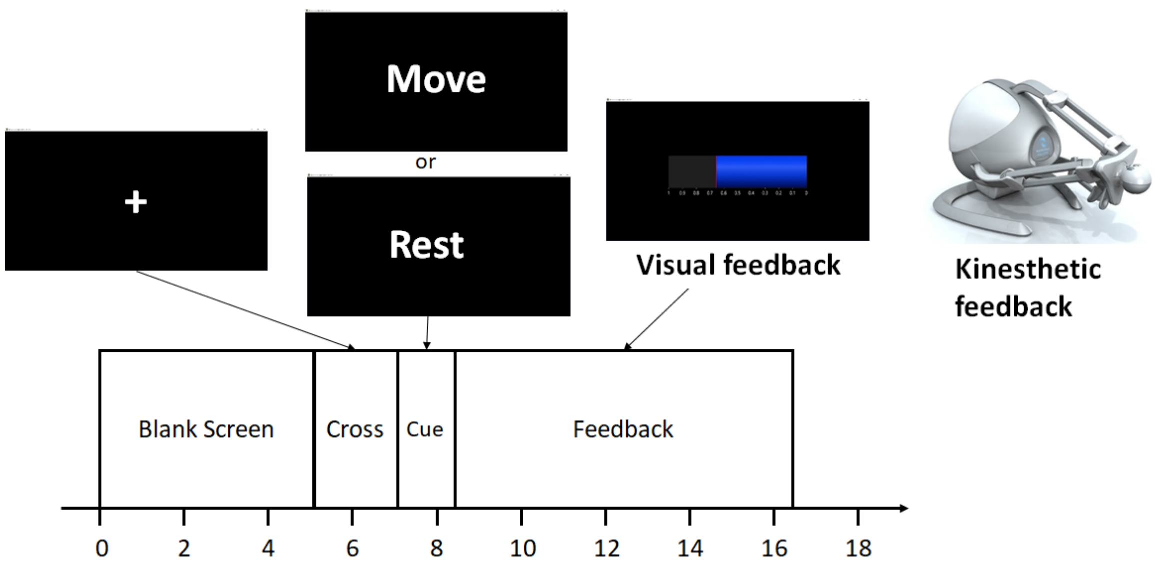

Figure 5- 3 Timing diagram of an online BCI run

5.2.4 Measurements and Analysis

The effectiveness and participant experience of the feedback for the BCI training were evaluated in the following ways.

BCI Classification Accuracy

BCI classification accuracy was calculated for each online BCI run as the percentage of the number of correct predictions of the BCI classification prediction divided by the total number of classification predictions. Pairwise comparisons with a 95% confidence level were made to analyze the effect of the visual feedback and kinesthetic haptic feedback on the classification accuracy by using a paired-samples t-test when the normality assumption was met and the Wilcoxon signed-rank test when it was not.

To determine if there was a significant improvement in classification accuracy across the runs, the BCI classification accuracy was entered into an analysis of variance (ANOVA) with a factor of runs (i.e., 1 to 12). Also, a simple linear regression modelling was used to examine the linear trends of the BCI training over time.

Spectral Band Power

To examine how brain activity differs between a motor imagery task with visual feedback and kinesthetic haptic feedback, power spectrum density, which represents the distribution of the EEG power in the frequency domain, was calculated and plotted for each individual. The plots of the power spectrum density were then visually analyzed 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 (Daly et al., 2014; Pfurtscheller & Neuper, 2010). The frequency bands selected were: the low-alpha band (8 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) (Yao et al., 2017). Pairwise comparisons with a 95% confidence level were made to analyze the effect of the feedback modalities on the BCI training by using a paired-samples t-test in each frequency band.

NASA-TLX

NASA-TLX (NASA-Task Load Index) is a commonly used method to evaluate subjective mental workload when using human technology interfaces (Miyake, 2015). It analyzes the workload in six different aspects: Mental Demand, Physical Demand, Temporal Demand, Own Performance, Effort, and Frustration Level (Hart & Staveland, 1988). The participants were asked to rate the workload of the system using scales from 0 to 20 on each workload aspect, on a printed form of the NASA-TLX after each feedback condition. Questions asked were as follows:

1. How mentally demanding was the task? (Mental Demand)
2. How physically demanding was the task? (Physical Demand)
3. How hurried or rushed was the pace of the task? (Temporal Demand)
4. How successful were you in accomplishing what you were asked to do? (Own Performance)
5. How hard did you have to work to accomplish your level of performance? (Effort)
6. How insecure, discouraged, irritated, stressed, and annoyed were you? (Frustration Level)

The scores of each aspect were averaged over the participants to determine the mental workload of the task for both of the feedback conditions. Related comments were transcribed.

5.3 Results

5.3.1 BCI Classification Accuracy

Table 5-1 shows the BCI classification accuracy in the online runs for the visual and kinesthetic haptic feedback for each participant. Comparing the accuracy between the visual and kinesthetic haptic feedback among participants individually, 7 out of 10 participants had better accuracy with the kinesthetic haptic feedback than the visual feedback (i.e., P1, P2, P3, P5, P6, P7, and P8), and for 5 of them, the accuracy was significantly higher. Participants P9 and P10 had higher accuracy with the visual feedback, but only P9 showed a significant difference between the two conditions. The accuracy of P4 was nearly the same in both conditions. By testing group differences in the feedback conditions using t-tests, the BCI classification accuracy with the kinesthetic haptic feedback was significantly higher than the accuracy with the visual feedback ($p=0.01$).

Table 5- 1 BCI classification accuracy of the visual feedback and the kinesthetic haptic feedback of all the participants and results of the paired-samples t-test

	Visual feedback		Kinesthetic haptic feedback		
Subject	**M**	**SD**	**M**	**SD**	**P value**
P1	69.25	5.33	88.54*	6.65	0.01
P2	56.56	15.68	78.63*	16.43	0.02
P3	69.38	10.99	77.08	8.90	0.07
P4	67.83	8.36	68.54	12.72	0.87
P5	60.71	5.79	65.54	7.58	0.09
P6	63.67	6.61	78.83*	5.82	0.01
P7	53.58	5.06	60.33*	6.64	0.02
P8	81.17	9.54	93.83*	2.46	0.01
P9	90.28*	3.74	84.17	5.89	0.02
P10	60.44	6.63	55.78	6.88	0.16
Average	**66.85**	**12.77**	**75.17***	**13.99**	**0.01**

** Significant differences p < 0.05 and NA: Not Applicable*

Figure 5-4 shows the average BCI classification accuracy for all the participants on each BCI run for both feedback conditions. The ANOVA revealed that there was no significant difference in the BCI classification accuracy across the runs for either feedback modality (F[11, 108]=0.19, p=0.99 for the visual feedback and F[11, 108]=0.31, p=0.98 for the kinesthetic haptic feedback). The regression line of the average BCI 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 kinesthetic haptic feedback).

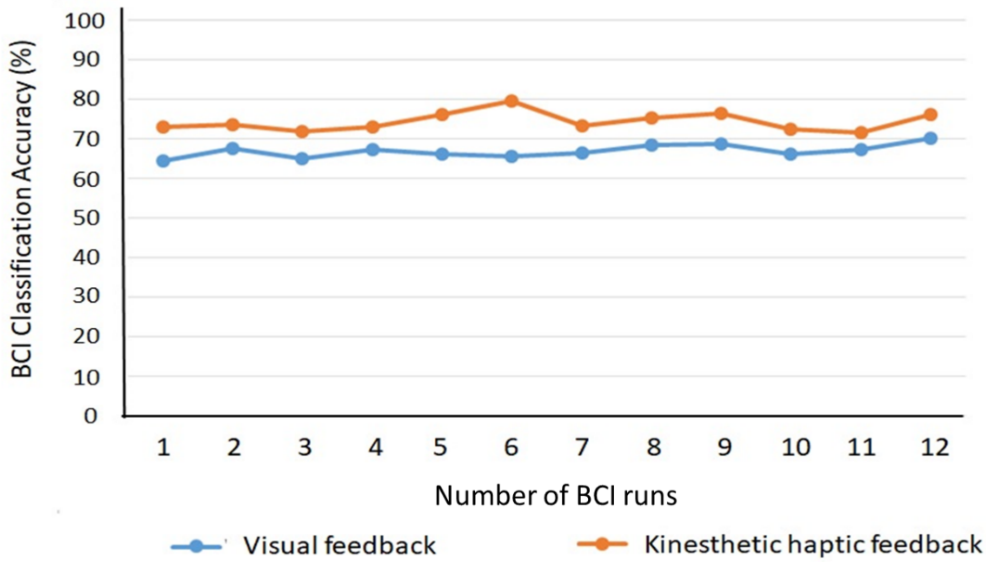

Figure 5- 4 Average BCI classification accuracy across the 12 runs for adult participants without impairments

5.3.2 Spectral Band Power

Figure 5-5 shows the power spectrum density of the C3 EEG channel for the run with the median BCI 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 the motor imagery. From the figure, the participants show three types of responses: 1) a power decrease in the alpha frequency during MOVE (e.g., P3, P6, and P9), 2) a power increase in the beta frequency band during MOVE (e.g., P1, P2, P4, and P8), and 3) a small difference between REST and MOVE in both feedback conditions (e.g., P5, P7, and P10).

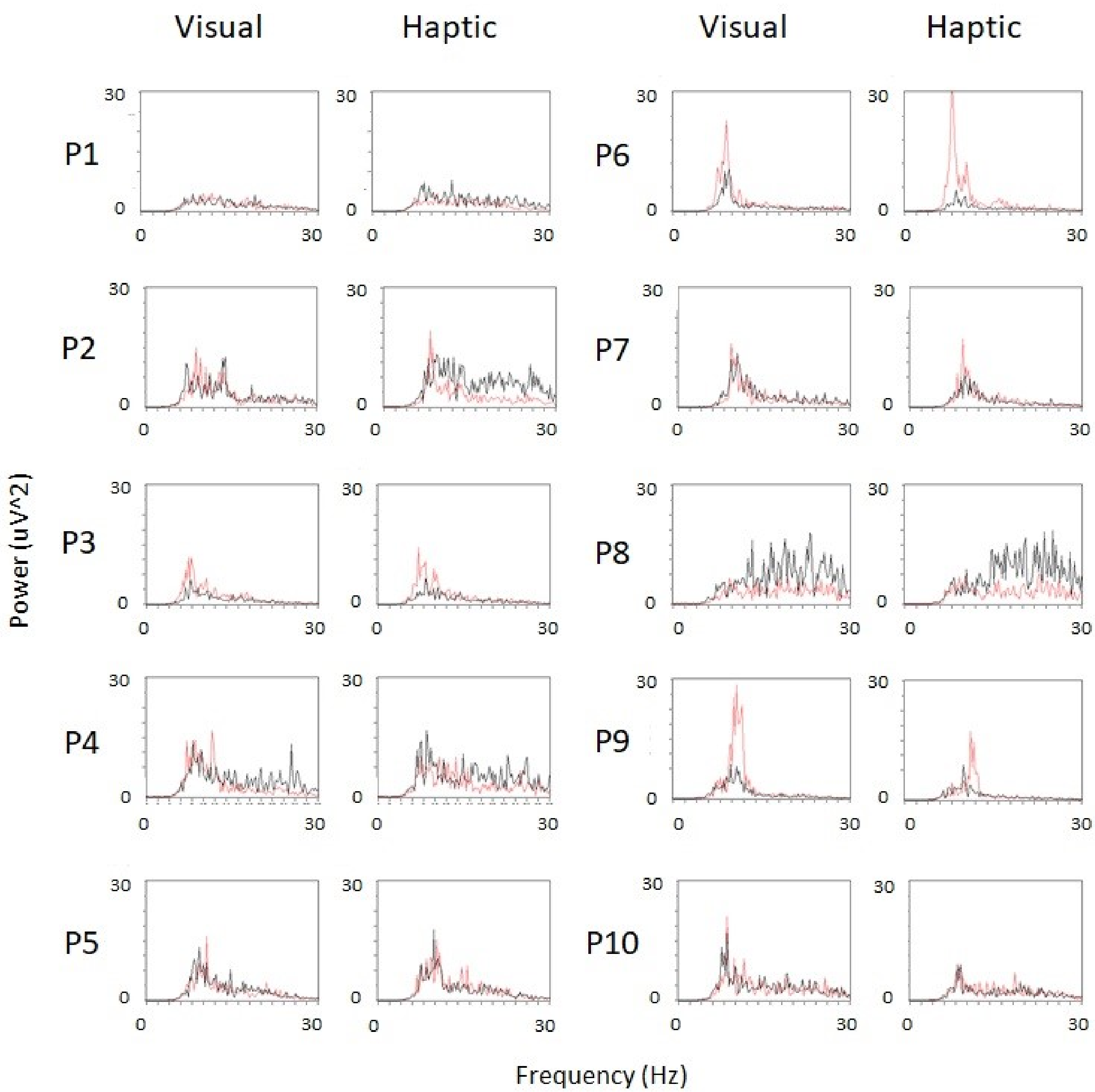

Figure 5- 5 Power spectrum density of the EEG channel C3 during MOVE (blue line) and REST (red line) for the two feedback conditions for the adults without impairments

Figure 5-6 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 of the t-test are summarized in Table 5-2, and a significant difference was found in at least one of the power bands in 7 out of 10 of the participants (i.e., P1, P2, P4, P6, P7, P8, and P9).

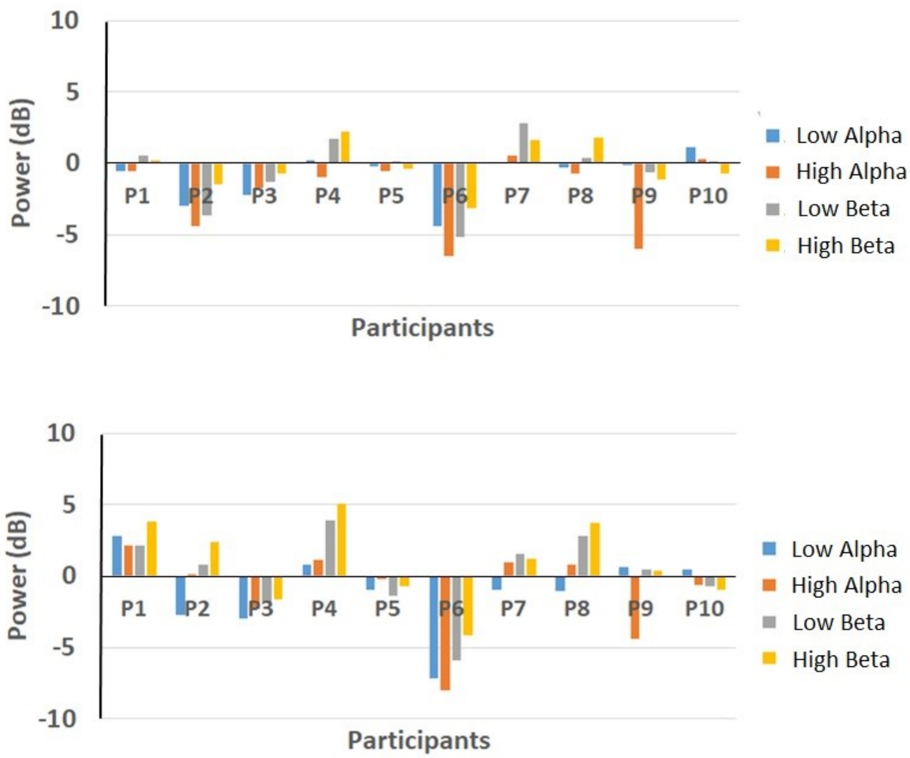

Figure 5- 6 Spectral band power differences from REST to MOVE of the visual feedback (top) and kinesthetic haptic feedback (bottom) for all of the adults without impairments

Table 5- 2 Results of the paired-samples t-test between the visual feedback and kinesthetic haptic feedback on each adult participant without impairments

Subjects	Low-α	High- α	Low-β	High- β
P1	0.01*	0.02*	0.05	0.01*
P2	0.96	0.45	0.04*	0.58
P3	0.98	0.95	0.75	0.23
P4	0.20	0.90	0.06	0.01*
P5	0.21	0.22	0.43	0.49
P6	0.01*	0.24	0.36	0.08
P7	0.03*	0.08	0.39	0.35
P8	0.73	0.63	0.01*	0.01*
P9	0.56	0.04*	0.81	0.12
P10	0.34	0.54	0.77	0.88

** Significant differences $p < 0.05$*

5.3.3 NASA-TLX

Figure 5-7 shows the average scores of the six workload aspects evaluated by the participants. In all six workload aspects, the score of the workload with kinesthetic haptic feedback was lower than with visual feedback. One participant commented that she preferred kinesthetic haptic feedback because she could feel her arm moving from left to right, 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 kinesthetic haptic feedback required less concentration during the task. However, another participant commented that the kinesthetic haptic feedback was very distracting during the REST phase when the EEG signal was incorrectly classified and the haptic robot interface moved.

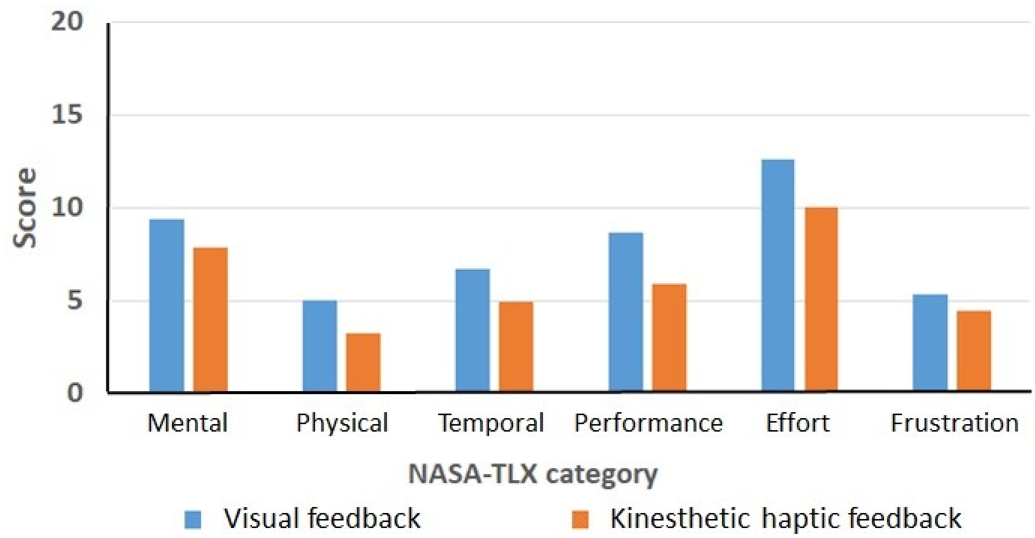

Figure 5- 7 Average scores of each aspect of NASA-TLX for the adult participant without impairments

5.4 Discussion

The BCI classification accuracy varied considerably between individuals. The participant who had high accuracy using visual feedback also had high accuracy using the kinesthetic haptic feedback. However, there was a trend where the kinesthetic haptic feedback generally led to a higher accuracy than the visual feedback, and the average accuracy over all the participants was significantly higher for kinesthetic haptic feedback. Thus, BCI training with the kinesthetic haptic feedback may help to increase the BCI classification accuracy and effective compared to the traditional BCI training protocol where the only visual feedback is used.

No significant improvement in the BCI classification accuracy across the runs was found in either feedback conditions over the 12 online runs. Even though a positive linear trend for the BCI classification accuracy was found for both feedback conditions, the slope values were not large. The literature about BCI training by Neuper and Pfurtscheller (2010) says 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. The training given in previous BCI studies was from a few BCI runs in one day session to more than 50 runs over several months (Jeunet et al., 2016; Pfurtscheller, Neuper, Guger, Harkam, Ramoser, Schlogl, et al., 2000).

The three types of brain patterns that were seen in the power spectrum analysis of the participants relate to the ERD and ERS responses. The power decreases in the alpha band can be considered the ERD response, and the power increases in the beta band can be considered the ERS response. To classify the motor imagery task, it is essential to have a clear difference in the brain patterns between MOVE and REST. As seen in Table 5-1, the participants who were in the Type 1 or 2 brain patterns, tended to perform motor imagery task with better BCI classification accuracy than the participants of Type 3.

In the comparison of the spectral band power differences from REST to MOVE in the four different frequency bands, significant differences were observed in 7 out of 10 participants. Interestingly, 5 of them had a significantly higher BCI classification accuracy for the kinesthetic haptic feedback (i.e., P1, P2, P6, P7, and P8). This implies that spectral band power differences from REST to MOVE in the four frequency bands had a strong influence on the BCI classification accuracy. The premise in the study by Pfurtscheller and Neuper (2010) about the ERD/ERS response not only being related to active movement or motor imagery but also to passive movement, was beneficial in the BCI training in this study. From our results, it can be seen that the ERD and ERS were induced by the kinesthetic haptic feedback when there was passive movement. This leads to distinguishable brain patterns to detect the movement intention and resulted in a better BCI classification accuracy.

Lastly, the motor imagery task with kinesthetic haptic feedback required less workload than the task with the visual feedback for the participants in this study. The kinesthetic haptic feedback had advantages like the reinforcing effect of the actual movement of their arm during motor imagery, and it had disadvantages like the distraction when signals were misclassified. However, the visual feedback tended to be quite fatiguing for the participants. Since a lower mental workload of the motor imagery task and higher BCI classification accuracy with the kinesthetic haptic feedback was found in this study, replacing the conventional visual feedback of the BCI training with kinesthetic haptic feedback could be a potential solution to improving the classification accuracy when using a BCI system for users in general.

Study 2

In the second study, the BCI system was modified to a game-like task for children without impairments and an adult with physical impairments. Because the motor imagery-based BCI training protocol is generally said to be time-consuming and tedious (Atyabi, Fitzgibbon, & Powers, 2012), the system was modified in order to make it more motivating and playful. The experimental setup was identical to Study 1 with the exception that instead of the simple bar indicator, a car was displayed on the computer screen and moved during the motor imagery task for the visual and kinesthetic haptic feedback conditions (See Figure 5-8). The measurements and data analysis were the same as the ones used in Study 1, however, the participants' performance was evaluated based on descriptive statistics due to the low sample size. A picture of the system is shown in Figure 5-9.

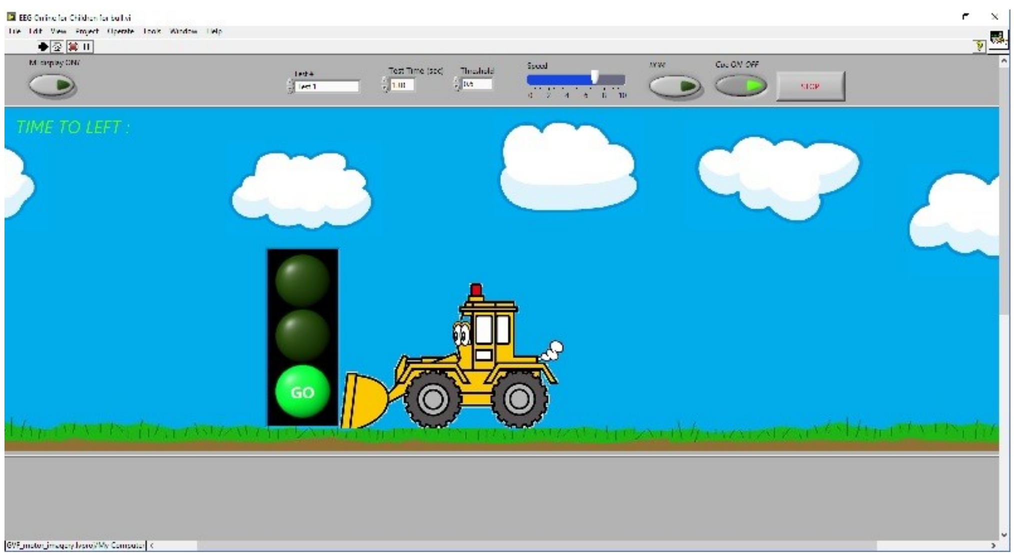

Figure 5- 8 The graphical user interface of the experiment for children and adult with physical impairments

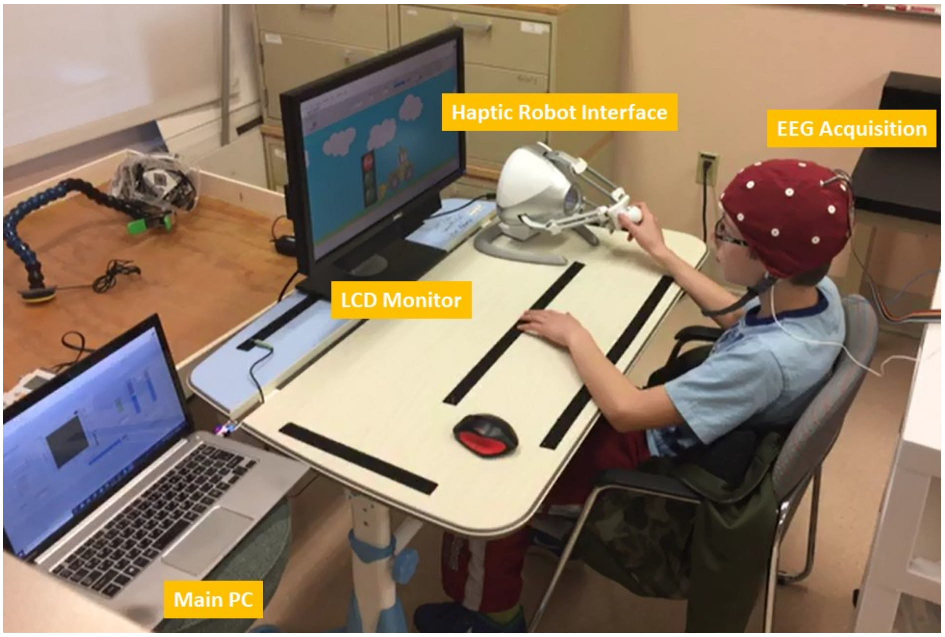

Figure 5- 9 Picture of the BCI system for children and adult with physical impairments

5.5 Methods

5.5.1 Participants

The system was tested by one 10 year, 2 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) (Palisano, Rosenbaum, Bartlett, & Livingston, 2007), and Level III according to the Manual Ability Classification System (MACS) (Eliasson et al., 2006). This classification means that she performs self-mobility by using a powered wheelchair and has difficulty handling objects. Ethical approval was received from the local Health Research Ethics Board Health Panel at the University of Alberta.

5.5.2 Procedures

Experiments

In this study, there were two sessions on different days. Each session lasted about one hour, including the system setup, one BCI classifier training and two online runs for each feedback condition. A total of only four online BCI runs for each modality were performed because in study

1 we found that providing 12 runs did not improve BCI classification accuracy for the adults without impairments. Two sessions were deemed to be not too much burden on the participants, but enough to explore the brain responses in this task.

During the BCI classifier training, the participants sat in front of a monitor and performed the motor imagery task according to a traffic light displayed on the monitor. The task cues were green light for MOVE, yellow light for READY, and red light for STOP. The cue was randomly repeated 6 times in each run. The sequence of the cue was as follows: 1) 5 seconds of all the lights off, 2) 2 seconds of the yellow light on, 3) 6 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. When the red light was on, the car stayed still, and the participants were asked to imagine no movement. For the kinesthetic haptic feedback condition, the participants held 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.

For the online runs, the participants drove the car with their motor imagery. The car only moved from right to left when the system detected the motor imagery with the same confidence levels used as in study 1. Otherwise, the procedure was the same as in Study 1.

5.5.3 Measurements and Analysis

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

5.6 Results

5.6.1 BCI Classification Accuracy

Table 5-3 shows the average BCI classification accuracy of the online runs for the visual and kinesthetic haptic feedback for the child participant without impairments, C1, and the adult with physical impairment, AD1. Their mean BCI classification accuracies were higher with the kinesthetic haptic feedback than the visual feedback. However, it can be seen in Figure 5-10 that the trend of their BCI classification accuracies declined 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 kinesthetic haptic feedback, and for AD1 the slope decreased by -2.1 for the visual feedback and -4.2 for the kinesthetic haptic feedback).

Table 5- 3 BCI classification accuracy of the visual feedback and the kinesthetic haptic feedback of both participants

	Accuracy for visual feedback		Accuracy for Kinesthetic haptic feedback	
Subject	**M**	**SD**	**M**	**SD**
C1	57.25	8.73	64.63	8.63
AD1	60.25	5.87	66.5	6.74

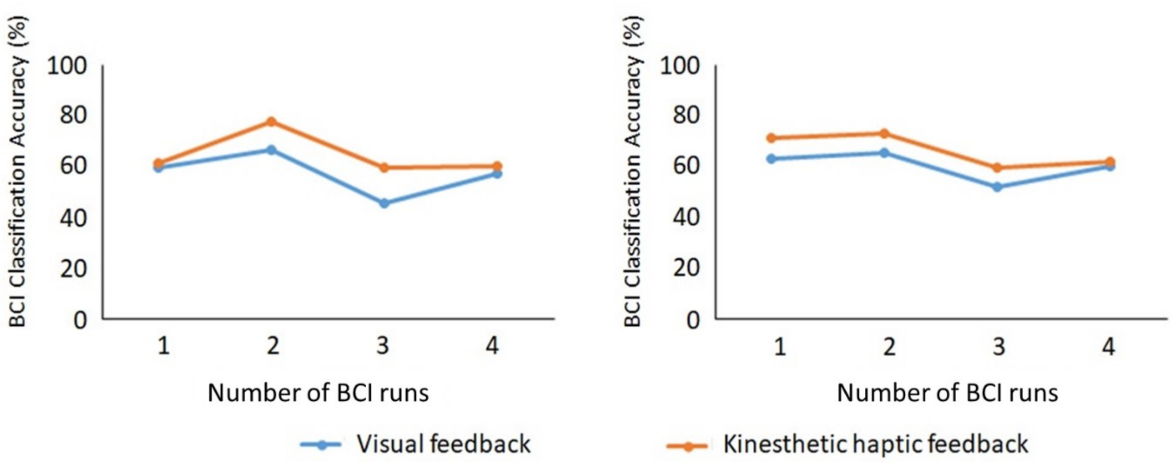

Figure 5- 10 BCI classification accuracy across the 4 runs with each feedback modality for C1 (left) and AD1 (right)

5.6.2 Spectral Band Power

Figure 5-11 shows the power spectrum density in channel C3 for the run with the median BCI classification accuracy for both participants, and a peak frequency on the power spectrum density can be seen in both feedback conditions. The power spectrum density of C1 shows the spectrum patterns during MOVE and REST were quite similar. On the other hand, AD1 shows a clear peak frequency around 13.5 Hz, and the amplitude of the peak increased during the REST and decreased during the MOVE.

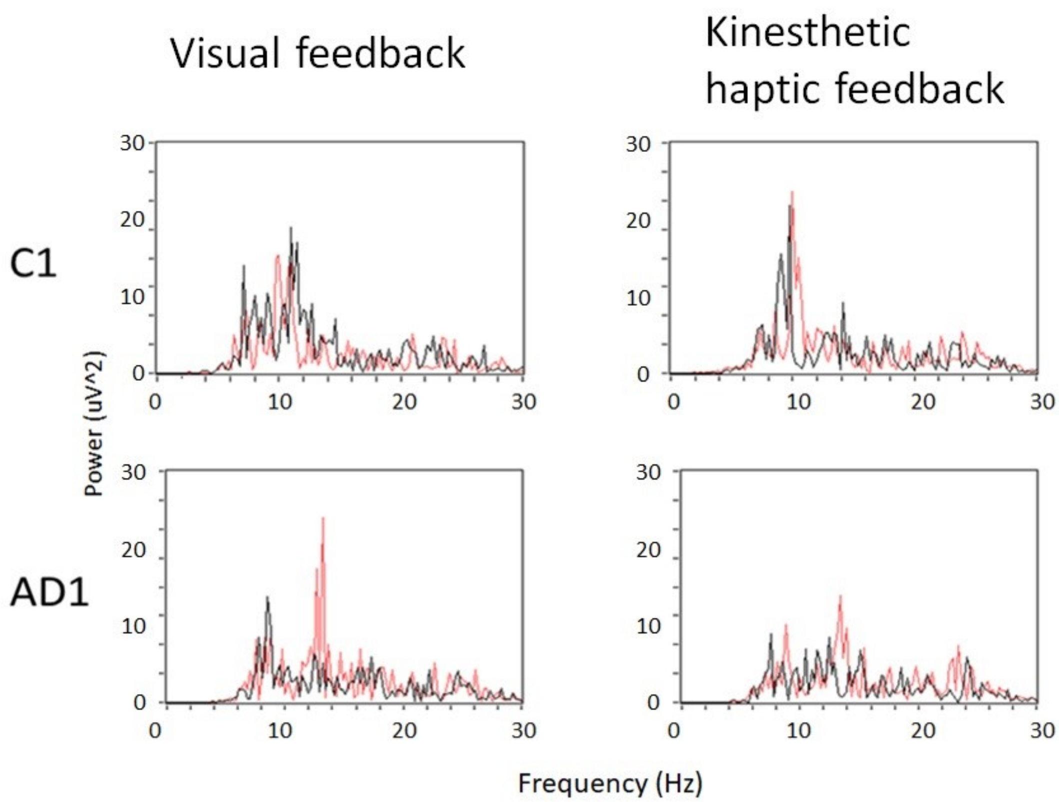

Figure 5- 11 Power spectrum density of the EEG channel C3 during MOVE (blue line) and REST (red line) for C1 and AD1

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 5-12. For C1, the expected band power decreases for MOVE appeared in the high-alpha frequency band, and expected increases appeared in the low and high-beta frequency band, for both feedback conditions.

However, the amplitude of the power differences 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.

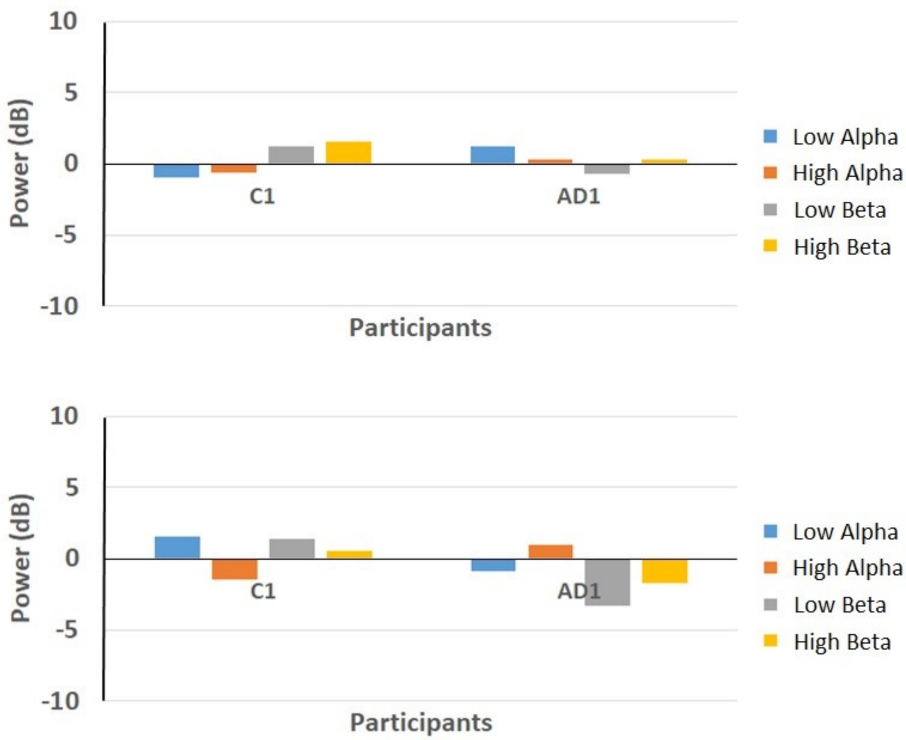

Figure 5- 12 Spectral band power of the visual feedback (Top) and kinesthetic haptic feedback (Bottom) for C1 and AD1

5.6.3 NASA-TLX

For C1 and AD1, the workload scores of the kinesthetic haptic feedback were equal or lower than the scores for visual feedback (see Figure 5-13). Small score differences between the two feedback conditions were observed from C1, however, larger score differences on the mental demand, performance, effort, and frustration were reported by AD1. At the second session, AD1 commented that she felt tired when she went home after the first session, though she did not realize how tired she was during the session.

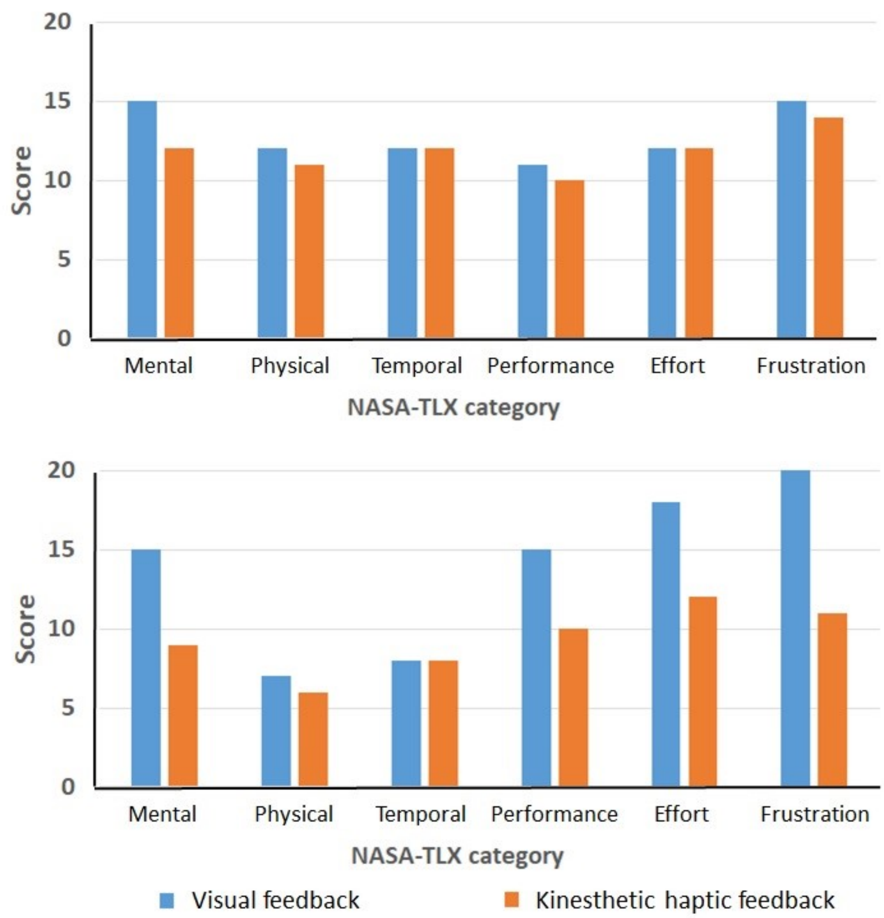

Figure 5- 13 NASA-TLX score of each workload aspect for C1 (top) and AD1 (bottom)

5.7 Discussion

BCI training using kinesthetic haptic feedback provided significantly more accurate classification than conventional visual feedback for ten adult participants without impairments. Similar to the adults without impairments, the child participant and the adult who had disabilities appear to have had a higher BCI classification accuracy using the kinesthetic haptic feedback than using the visual feedback for all the runs. Thus, the kinesthetic haptic feedback was effective for improving the BCI classification accuracy during motor imagery for the child participant and the adult with physical impairments. Though we expected improvements in accuracy over time, C1 and AD1 actually showed a slight decrease in BCI classification accuracy over the 4 runs. The sample of study 2 may be too small to discuss the effect of the BCI training over time for those population, however, as mentioned in Study 1, they may need more runs in order to see an improvement in BCI performance.

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 Berchicci et al. (2011), the ERD response can be observed even in infants, and generally, the peak frequency of the ERD gradually increases until the age of about 5, so the EEG of the 10-year-old boy should be close to that of adults. Thus, his power spectrum density would be categorized in the pattern of Type 3 in Study 1. On the other hand, AD1 showed a peak frequency of around 13.5Hz in her power spectrum density in both conditions. Because the boundary of the frequency range between alpha and beta band was set to be 13 Hz, this peak frequency was classified as the low-beta band in this study. As seen in Figure 5-11, AD1, the amplitude of the low-beta peak increased during REST and decreased during MOVE. From such a behaviour, this peak should be considered her 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 of REST and MOVE. There was more potential to acquire distorted EEG signals from AD1 because she often made reactive movements when she realized that the system misclassified her movement intention during the task. These reactive movements caused muscular artifact in her EEG signals. However, by using the temporal and spatial filters to minimize the artifact and noise, her ERD was still detected with this BCI system. Thus, if classifiers are trained for each person individually, our proposed BCI system should be able to handle individual differences.

The NASA-TLX scores of C1 and AD1 have a similar trend to the adult participants without impairments in Study 1 with the scores being higher for the visual feedback than the kinesthetic haptic feedback, though the scores are higher than those of the adult participants without impairments. This could be because of having less tolerance to wearing the uncomfortable EEG cap, concentrating during the motor imagery task, or fixation of the body posture required during the task to avoid muscular artifact. The one-hour session may have been too long for C1 and AD1, judging from the comment of AD1 about being tired. BCI tasks require focused attention, and the long BCI sessions often make participants feel tired (Atyabi et al., 2012). 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 ideal for BCI sessions with children and adults with disabilities.

This study has limitations, which should be acknowledged. First, due to the small sample size, the data can serve only as preliminary data suggesting further research. Secondly, the participants in study 2 were asked to drive the car displayed on the screen with their motor imagery, whereas the participants in Study 1 controlled the value of the bar indicator. Although the BCI classification accuracy between the two studies may not be comparable in the strict sense, the data suggests that the BCI system in Study 2 seemed to work to have the same effect as the Study 1. Lastly, because of the nature of the game-like graphical user interface, the participants had the visual feedback at the same time as the kinesthetic haptic feedback during the task in the Study 2, whereas the participants in Study 1 only had the kinesthetic haptic feedback. The multimodal feedback may have resulted in higher BCI classification accuracy than the single mode feedback in Study 1 (Angulo-Sherman & Gutiérrez, 2014). However, the results in Study 2 helped to explore the potential of using the proposed BCI system with a younger population and a population of people with physical impairments.

5.8 Conclusion

The use of kinesthetic haptic feedback with a BCI system resulted in a significantly higher BCI classification accuracy than using visual feedback in the study when the system was tested with adults without impairments. Visual analysis of the data from a child and an individual with impairments also indicated a higher BCI classification accuracy with the kinesthetic haptic feedback than the visual feedback. Due to the lower workload required while doing the kinesthetic haptic feedback, the kinesthetic haptic feedback could be a feasible method for the BCI training. However, no significant improvement of BCI performance was found, even after 12 online runs of the BCI training, in either haptic or visual feedback conditions. Providing training for several months could be beneficial to examine the potential for improvements in both feedback modalities. Also, there is need for the further research to explore using the kinesthetic haptic feedback for people with physical impairments. The proposed BCI system was limited to binary classification of the movement intention (e.g., REST and MOVE), however, for applications such as robot or device control, which is more complex and requires more commands, the use of only BCI signals may not be enough. Integrating BCI with other human-technology interfaces using biological signals such as electromyography or eye gaze data could be studied in future research. Different interfaces could be used for different tasks or signals could be combined for redundancy to enhance the accuracy of the classifier.

Chapter 6

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

6.1 Introduction

The human-technology interface plays a fundamental role when controlling assistive technologies to perform functional activities. 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 (Cook & Polgar, 2008).

A common human-robot interface for people with impairments is a single button switch. This is the simplest type of switch 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. A study by Rios-Rincon, Adams, Magill-Evans, and Cook (2016) successfully demonstrated robot control by four children with cerebral palsy using three single button switches for "forward", "left turn", and "right turn".

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 (Cook & Polgar, 2014). Song and Kim (2013) developed a self-feeding robot for people with physical disabilities who have limited arm function. The system had two different types of input methods (i.e., switches and 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 assisting people with limited or no upper limb mobility to achieve activities of their daily living, is sold with a joystick controller (Maheu, Frappier, Archambault, & Routhier, 2011). 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 to many people, this biological signal 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 (Zander, Gaertner, Kothe, & Vilimek, 2011). Arai and Yajima (2011) developed a feeding aid system using 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 reach it. In Encarnação et al. (2017), 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 type of biological signals-based device control in recent years (McFarland & Wolpaw, 2011). Electroencephalography (EEG) is a non-invasive method to record the brain's activity with electrodes placed on the surface of the scalp (Nunez & Srinivasan, 2006). EEG can be used to detect the brain activity associated with real or imagined movement, which produces changes in the sensorimotor rhythms. Sensory processing or 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) (Pfurtscheller & Neuper, 2010). The signals can be detected and classified as physical movement, motor imagery or rest using machine learning methods, and then used to control technology. D. Huang et al. (2009) tested BCIs for 2-dimensional cursor control based on ERD and ERS during motor execution and motor imagery with five participants without impairments. In Cincotti et al. (2008), 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. (2012) developed a gaze and ERD-based BCI driven controller for an exoskeleton for stroke rehabilitation to assist the movement of the upper limb in reaching. An integrated system such as this could be a solution for children with severe physical impairments to control assistive robots for play: eye tracking can be used to detect a desired target or destination, and the BCI could be used to move the robot towards the target or destination.

In order to use such a system to control a robot in a physical environment, certain issues need 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. Users are typically 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 another layer of complexity (Encarnação et al., 2017). 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 (Burke et al., 2006) and off-screen interaction studied in Chapter 3.

BCI using ERD/ERS has the advantage of not needing a stimulus as 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 is not 100%. Increasing the classification accuracy of the user's movement intention with the BCI is a crucial challenge for reliable device control. Kinesthetic haptic feedback while imagining movements could help to improve the BCI classification accuracy. Chapter 5 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. This approach was chosen based on the finding of Gomez-Rodriguez et al. (2010) that passive movements induced EEG patterns similar to those observed during motor imagery. The classification accuracy using the system with the 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:

1. Can haptic feedback (vibrotactile haptic feedback for eye gaze to select targets and kinesthetic haptic feedback for motor imagery for driving a robot) from the integrated eye gaze and BCI-based human-robot interface make functional robot tasks faster?

2. Can haptic feedback lead to a lower workload in the functional robot task compared to without it?

6.2 Methods

6.2.1 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 with a 52-year-old female with quadriplegic cerebral palsy (AD1) who had difficulty handling objects and has been classified as Level IV in the Gross Motor Function Classification System Expanded and Revised (GMFCS-E&R) (Palisano et al., 2007), and Level III according to the Manual Ability Classification System (MACS) (Eliasson et al., 2006). 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 a previous study in Chapter 3 and Chapter 4. Ethical approval was received from the local Health Research Ethics Board at the University of Alberta.

6.2.2 Experimental Setup

The experimental setup of this study consisted of four components, an eye tracking system, a BCI system, a haptic feedback system, and a mobile robot as shown in Figure 6-1. A picture of the whole system is shown in Figure 6-2. Details of each system are described below.

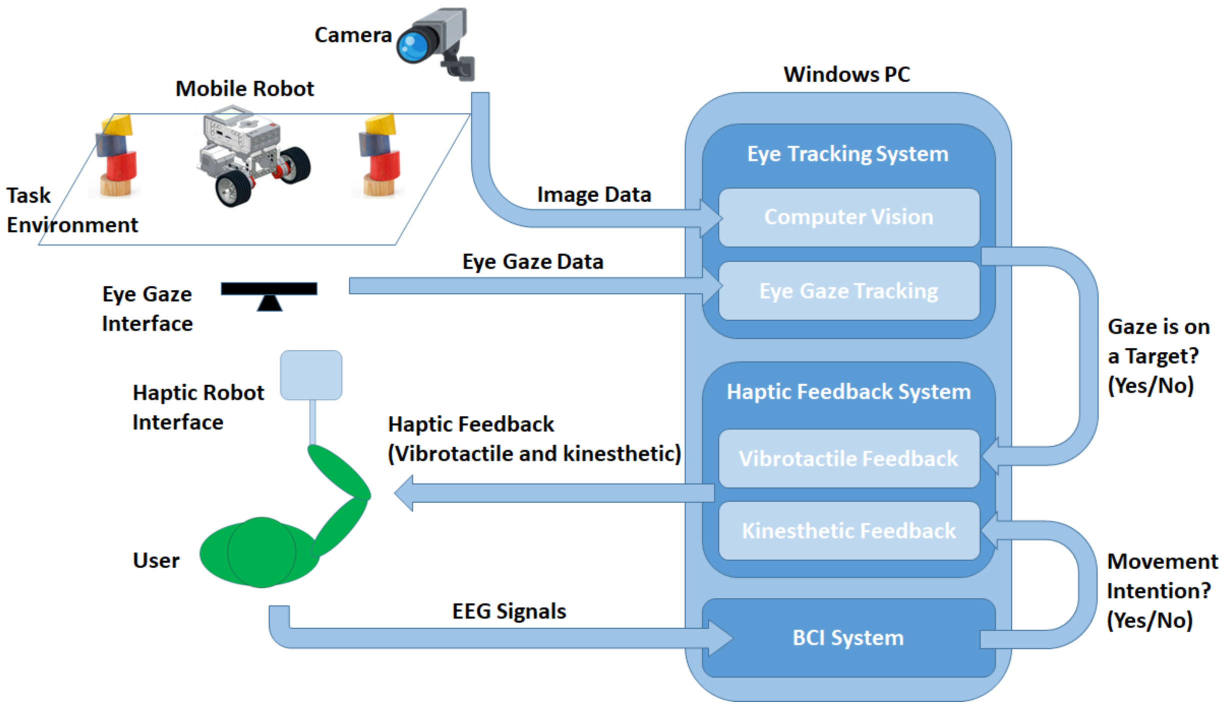

Figure 6- 1 Schematic diagram of the system in interaction with the user and the task environment.

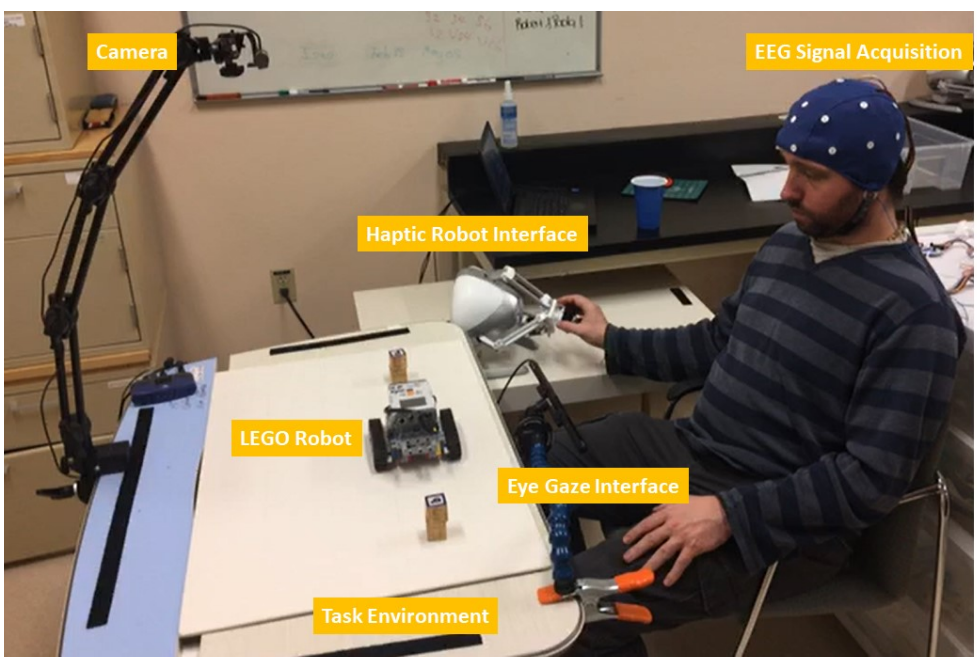

Figure 6- 2 Picture of the system with the human-robot interface and the task environment.

Eye Tracking System

The 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. A USB camera (Dynex, Richfield, MN, USA) was mounted over the task environment, which acquired the image data of the entire 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 6-3. The 3 x 3 homogeneous transformation matrix was obtained by solving the following linear equation (Szeliski, 2011):

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{6.1}$$

Where $[x \quad y \quad 1]^T$ represents the gaze position data when the participant is looking a calibration point and $[x' \quad y' \quad 1]^T$ represents a location of the calibration point captured by the USB camera.

Objects in the task environment were detected by an object recognition program coded in LabVIEW, and the locations were obtained. When the participants want to select a target in the task environment, they need 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 (Bednarik et al., 2009), but 1.5 seconds was selected in this study to make sure participants had enough time to select the target, based on a 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.

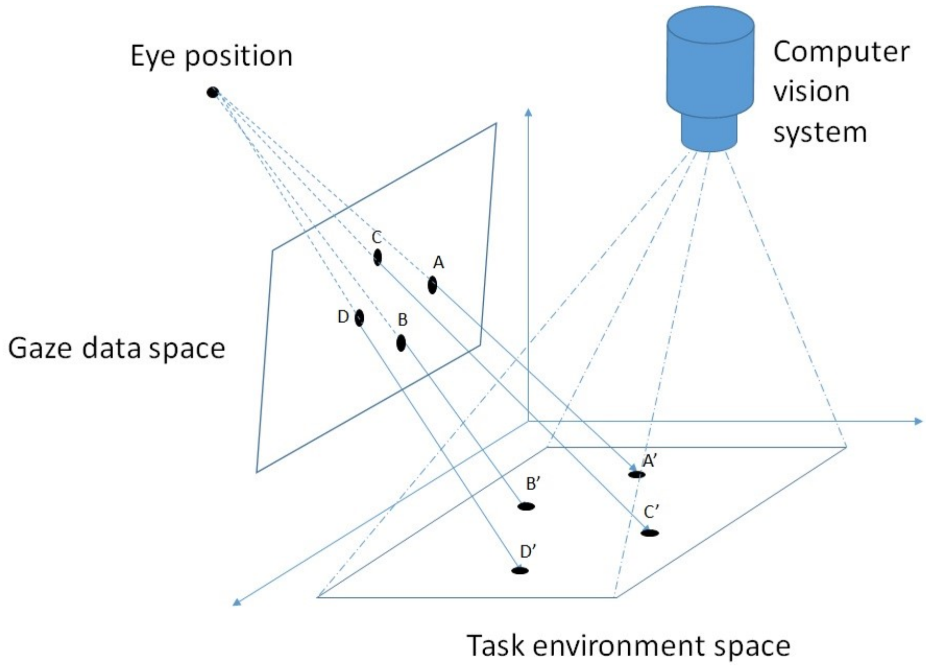

Figure 6- 3 Points in the eye tracker space and environment frames, which were related by a transformation.

Brain-Computer Interface (BCI) System

The BCI system included OpenBCI hardware (OpenBCI, Inc., Brooklyn, NY, USA) and OpenViBE software (Renard et al., 2010). OpenBCI was used to measure the participant's EEG signals for robot operation. 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 (i.e., Cz, Cp, F3, C3, P3, F4, C4 and P4 of the international 10-20 system), which is responsible for motor-related activities, were recorded at a sampling frequency of 250 Hz. 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 (Koles et al., 1990). The logarithmic power of the feature vector 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 our 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 (Romero-Laiseca et al., 2019).

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 on 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 the 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 move the participant's hand, which was placed on top of the user interface, and this provided kinesthetic haptic feedback about the EEG signals. 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 was calculated in a 0 to 1 value range. When the confidence values were lower these matched the classification of REST, and when the confidence values were higher 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 facilitate the movement of the participant's hand. The force exerted on the haptic robot interface by participants was measured to ensure that they were moving it by their EEG motor imagery, not physically pushing the end-effecter of the interface. If an interaction force over 4N 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.

Mobile Robot

The mobile robot for the participant to control was a Lego Mindstorms NXT (LEGO System A/S, Billund, Denmark). It connected with the PC wirelessly via Bluetooth and was controlled based on the participant's eye gaze (target selection) and EEG signals (move towards the target). The Lego robot was placed between two piles of wooden blocks (see Figure 6-1 and Figure 6-2), and the task goal was to move the Lego robot to knock down one of the two piles of wooden blocks.

6.3 Procedures

6.3.1 Experiments

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. In this experiment, a modified version of the Graz BCI training protocol was used, which is one of the most widely used training protocols for BCI studies (Jeunet et al., 2016). As BCI training based on motor imagery is regarded as tedious and time-consuming, in order to make the training more motivating and sustain their attention, it was modified to a game-like scenario in Chapter 5. During the BCI training, a car displayed on the computer screen moved or stopped according to the traffic light on the screen (see Figure 6-4). 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.

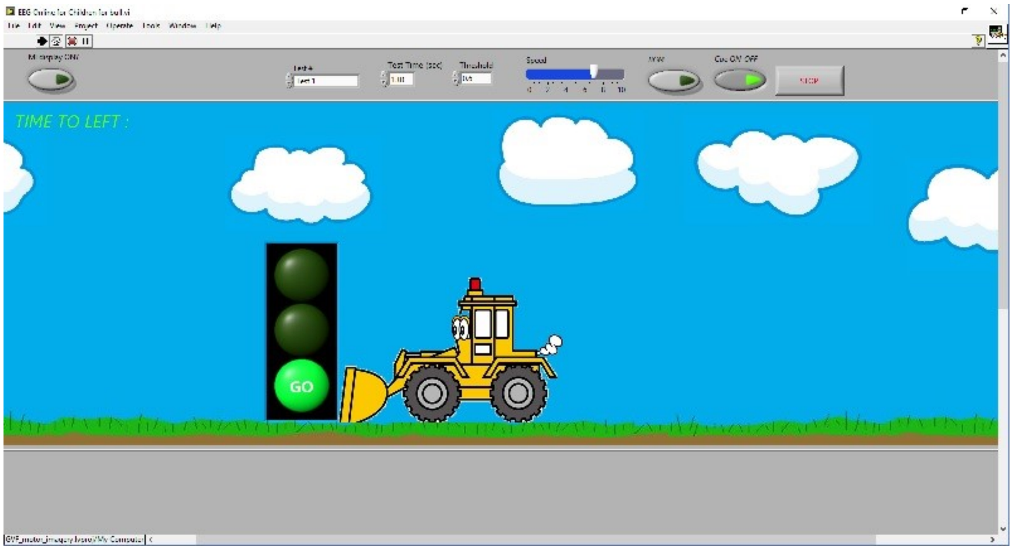

Figure 6- 4 Graphical user interface for the BCI training

After the training, the participant’s eye gaze was mapped to the task environment using homography. 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). This transformation matrix was used for mapping the eye tracker frame to the camera frame of the task environment.

The task steps were as follows: 1) The researcher gave verbal instructions to the participant about which pile of the blocks to knock down; 2) The participant fixated their gaze at the target block. When the system determined that the participant's gaze was on a target for more than the 1.5 second dwell time, a voice confirmation was given to the participant (i.e., "left target was selected" or "right target was selected"); 3) The participant then performed motor imagery of their dominant hand to drive the Lego robot until the target block was knocked down.

The task was done with and without feedback (both vibrotactile haptic 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 the target selection and the kinesthetic haptic feedback during the 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.

6.3.2 Measurements and Analysis

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

- **BCI classification accuracy:** The classification accuracy of MOVE and REST based on EEG signals acquired in the BCI training was calculated using 5-fold cross-validation.
- **Overall task completion time (measured in milliseconds):** The time from the task cue until the robot knocked down the blocks. The task in this study was further divided into two parts: time to select the target using eye gaze **(Target selection time)** and time to knock over the blocks with the robot (**Robot driving time)**.
- **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 completion time, the target selection time, and robot driving time 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.

6.4 Results

6.4.1 BCI Classification Accuracy during Training

Table 6-1 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 6- 1 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

6.4.2 Task Completion Time

Figure 6-5 shows the overall task completion time of all the six participants. All the participants achieved the task with the haptic feedback (i.e., vibrotactile and kinesthetic) 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.

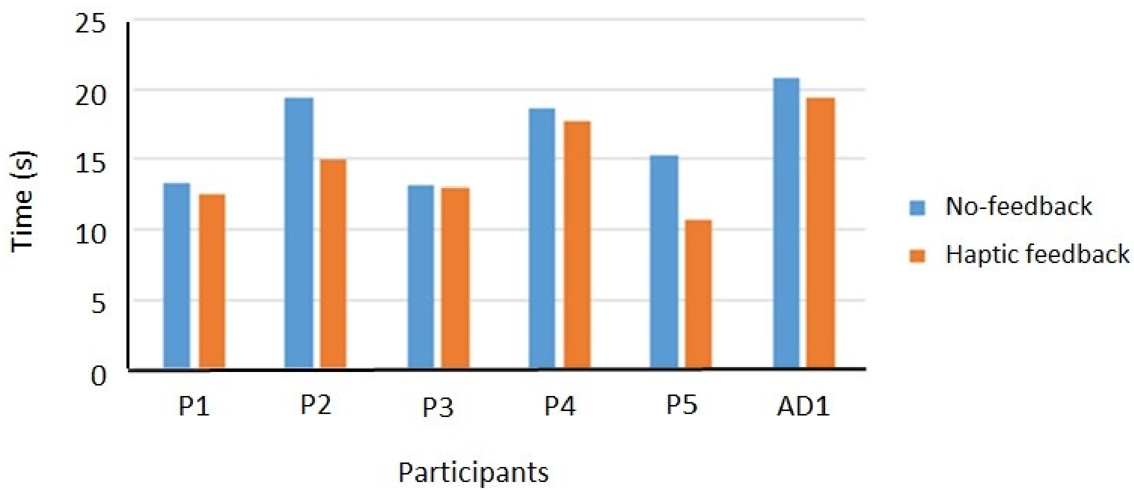

Figure 6- 5 Task completion time with the different task conditions for all the participants

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 6-6 (left), but the differences were very small. 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 6-6 (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.

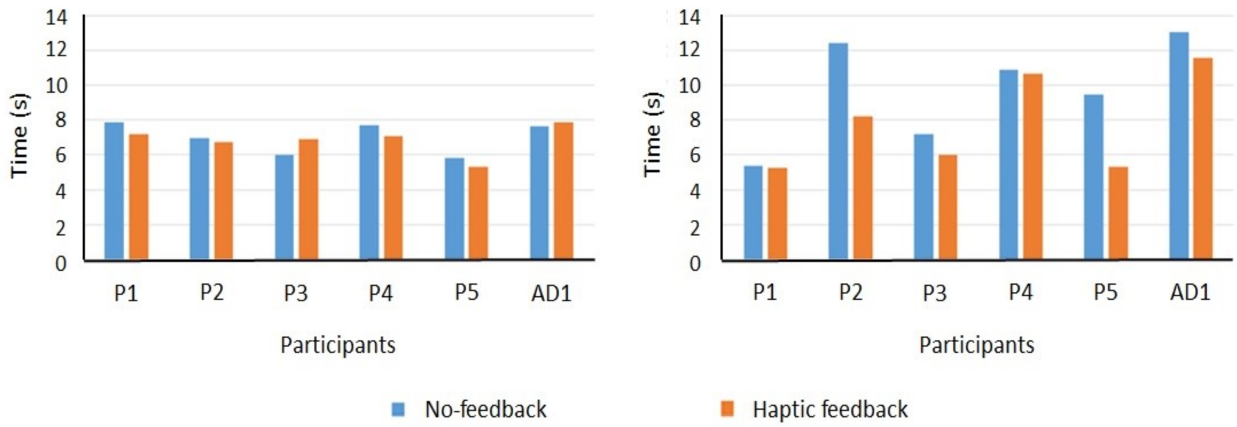

Figure 6- 6 Target selection time (left) and the robot driving time (right) with the different conditions for all the participants

6.4.3 NASA-TLX

Each participant's total score on all the six aspects of the NASA-TLX (120 points maximum) is summarized in Figure 6-7. 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. The score differences between the two task conditions for P1, P3, P4, and AD1 were relatively smaller than the score differences for P2 and P5. Participants commented that it was easy to use the human-robot interface 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.

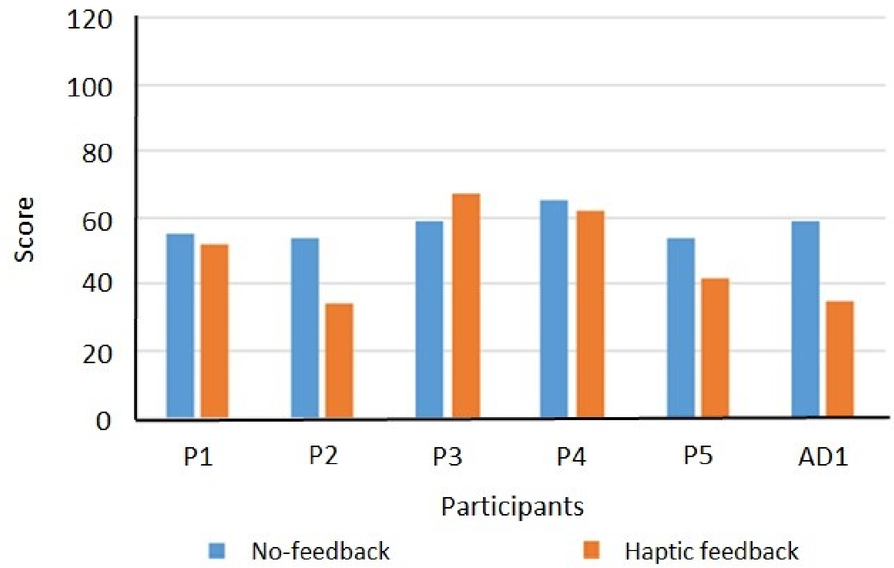

Figure 6- 7 Total score of the NASA-TLX ask with the different task conditions for all the participants

6.5 Discussion

The overall target selection and robot control task using the proposed human-robot interface was performed 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. There was no concern about the target acceptance area overlapping with other targets, but if there were more targets in the task environment, the acceptance size would have to be smaller to avoid selecting the wrong target. In that case, vibrotactile haptic feedback might have been helpful to attain the smaller targets, based on the results of Chapter 3. 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 and the feedback allowed her to perform the target selection using the gaze fixation in a comparable way to the participants without impairments.

Regarding driving the robot with motor imagery, it is to be noted that some confounding brain activation may have been elicited in supporting the arm against gravity while the participants were holding the end-effector of the Novint Falcon. Therefore, the brain activities collected in the kinesthetic haptic feedback condition may not be purely brain activities associated with arm movement from right to left following the Novint end-effector. Despite this, all the participants were able to drive the robot and knock down the target blocks faster in the task with the kinesthetic haptic feedback, although the difference was only statistically significant for two participants. This was expected based on the study by Gomez-Rodriguez et al. (2010) 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.

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.

6.6 Conclusion

In this study, an integrated eye gaze and BCI-based human-robot interface using haptic feedback was developed, and the effectiveness of the haptic feedback in a simple mobile robot control task was evaluated. Haptic feedback improved the performance in the overall task. 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 two participants showing significance. It will be an interesting technical challenge to overcome the low accuracy of gaze interaction in a real environment or BCI classification accuracy to achieve reliable robot operation (compensating for movement, signal noise, artifact). However, the 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. Natural physiological functions were used to accomplish the steps of the task, i.e., selecting targets with eye gaze, and moving via imagery of movement, and they were integrated into one system.

Chapter 7

General Discussion and Conclusion

Chapters 3 through 7 of this dissertation describe the development of a haptics-enabled human-robot interface. This human-robot interface enables a user to 1) select a target object or destination in the physical environment based on their eye gaze, and 2) move a robot towards the target on the basis of their movement imagery as captured via a BCI. In addition, this human-robot interface provided two types of haptic biofeedback to the user in order to improve the accuracy of the operation: 1) vibrotactile haptic feedback, which helps users to sustain their eye gaze on an object, and 2) kinesthetic haptic feedback, which facilitates the passive movement of their hand, based on the generated movement intention.

7.1 Eye Gaze Interface

To capture eye gaze, instead of using a head-mounted eye tracker to control the robot, the method typically used in physical-world gaze application research, we used an inexpensive stationary eye tracker. To use the stationary eye tracker, which is designed for on-screen gaze application, two features were implemented. First, a homogeneous transformation was used to map between the gaze direction detected by the eye tracker and the objects in the physical environment. Second, we added feedback if the system was detecting that the user's gaze was on a target object in the environment. The tests of the system showed that target selection in the physical environment was significantly slower than on-screen for adult participants without impairments, and slower for the children without impairments and adults with physical impairments, based on the descriptive analysis. Thus, when considering the final goal of the system, off-screen robot control for play for children with disabilities, we will have to take into account that off-screen tasks will be more difficult to perform than on-screen tasks.

In Chapter 3, the adult participants without impairments were able to accomplish the task in the physical environment without errors, while the children without impairments and adults with physical impairments showed some errors when the target was small. Part of the problem was that they had difficulty keeping their heads still during the gaze interaction trials. In particular, the adult with physical impairments, who is affected by strabismus, tended to move her head from side to side in an attempt to compensate for her vision problem during the trials. The child participant with physical impairments, who was diagnosed with ADHD, had great difficulty in keeping his head still and had a greater spread of vertical and horizontal eye movements than the participants without impairments. These behaviours may have had an impact, resulting in the higher timeout error rate of the adult and child with physical impairments than the participants without impairments. Prior to the experiment, when the system mapped the user's eye gaze into the task environment the eye gaze data were accurately calibrated, however, the occasional movements of their heads resulted in a loss of the calibration accuracy. Some studies have used a chin rest to stabilize the user's head to improve the accuracy of eye tracking (Santini & Rucci, 2007; Zhiwei, Qiang, & Bennett, 2006), however, the use of a chin rest would take away the user's natural gaze interaction with the objects in physical environment. A common feature in head-mounted eye trackers is a 3-dimentional accelerometer or inertial measurement unit (IMU), to detect the head position and compensate for the head movement during the gaze interaction; this helps to accurately determine from the camera view of the environment which object in the physical environment is being gazed upon (Linn et al., 2014). A similar technique could also be implemented in the system with stationary eye tracker to improve the accuracy of eye tracking (Al-Rahayfeh & Faezipour, 2015).

Visual feedback such as a cursor or pointer is commonly used to improve eye gaze interaction accuracy in on-screen applications. In this dissertation, we examined feedback that could be alternatives to visual feedback, so that it can be used in off- screen gaze applications. Similar to how Kangas et al. (2014) found better performance using visual feedback in on-screen applications compared to no feedback, auditory feedback and vibrotactile haptic feedback about gaze fixation made the gaze interaction performance statistically faster and more accurate compared with no-feedback in the off-screen applications in this dissertation. As far as spatial accuracy of the gaze interaction in the physical environment in Chapter 3, the smaller the target object size, the slower the users were to complete the target selection. These results were consistent with the Fitts' law expressing a tradeoff between time of movement and size of target indicating a notion of complexity for the pointing target task. The smallest target size that all of the participants tested in the gaze interaction in physical environment was 6 cm in diameter. With the no-feedback condition, all the target selection trials were successfully completed by the adults without impairments. On the other hand, there were timeout errors for the child and adult with physical impairments, but the timeout error rate decreased when the feedback was on. No significant difference was found in participant performance between the two feedbacks modalities. Similar results can be found in a study of Jussi Rantala et al. (2017), who reported that the performance of the on-screen gaze interaction among the different feedback modalities was equal. However, our results showed that the users themselves had personal preferences, with the vibrotactile haptic feedback being the most common. The results of Chapter 3 also imply that the participants were able to perform the cross-modal integration between the visual perception and auditory/vibrotactile information (seeing the environment and hearing/feeling feedback) during the gaze fixation in order to achieve target selection success. According to the results of the user's preference, the vibrotactile haptic feedback for the target selection was applied to the integrated system in Chapter 6.

In the eye gaze studies, the user was required to fixate their eye gaze for a prolonged period of time on the target to select it. This dwell selection time is one of the most common selection methods for on-screen gaze applications. A longer dwell time gives the users enough time to make sure they are selecting the correct target and avoid false selections. However, the longer dwell time requires more time to complete the target selection. A different approach for target selection could be utilized for the prediction of the user's gaze data using machine learning techniques (Castellanos, Gomez, & Adams, 2017; C.-M. Huang, Andrist, Sauppé, & Mutlu, 2015). For example, C.-M. Huang et al. (2015) investigated a way to quantify how eye gaze patterns may indicate a person's intention using a Support Vector Machine algorithm. The authors demonstrated 76% accuracy in predicting the user's target of interest, even a few hundred milliseconds before the user fixated their gaze on it. This approach could possibly make the gaze interaction faster, however, the study also reported that the user did not look only at the target of interest when the user wanted to select a target. Several gaze behaviours prevented the correct prediction. For example, saccades, rapid eye movements to quickly scan an area of interest, are random movements and difficult to differentiate from intended gaze behaviours. Thus, the machine learning prediction could result in selecting the wrong target, and thus is not reliable for use for robot control yet, especially for children who may not tolerate the errors well.

7.2 Brain-Computer Interface

Subsequently, we examined the feasibility of ERD/ERS-based BCI for robot control. In typical use, users can improve the ability of BCI control by monitoring visual feedback about how well they are performing the motor imagery displayed on a screen (Alimardani, Nishio, & Ishiguro, 2014). In many robot applications using BCI, users were often required to look at a computer screen where the video image of the robot and visual feedback about their brain activity was displayed (Pfurtscheller & Neuper, 2010), or they were required to directly look at the robot without having any feedback about the brain activity, except to see the consequences of the robot action (Cincotti et al., 2008).

In Chapter 5, we explored a method for users to directly interact with a robot using the BCI, and receive kinesthetic haptic feedback that facilitated their arm movement according to the detected movement intention. In this way, the users could feel the feedback about their motor imagery associated with body movement and operate a robot without needing visual feedback. Motor imagery-based kinesthetic guidance was studied by Gomez-Rodriguez et al. (2010) who reported that a passive movement facilitated by kinesthetic guidance in robot assisted rehabilitation exercises induced the brain activities similar to those observed during motor imagery. However, in that study the kinesthetic guidance was provided in addition to visual feedback as cross-modal integration. In the BCI test conducted in Chapter 5, BCI training using only kinesthetic haptic feedback was compared with the Graz BCI training protocol, which provides only visual feedback displayed on a screen. The classification accuracy with kinesthetic haptic feedback was significantly higher than the accuracy with the visual feedback implying that the participants may have perceived the sensory input that their own arm was moving which may have elicited the brain activity associated with motor imagery. The motor action and sensing of haptic information are processed within the central sulcus region, while visual and spatial information is processed in the occipital area located at the back of the brain. The fact that motor action and haptic sensation are processed in the same cortical region, resulting in enhancing perception and action coupling, could help explain the better classification accuracy with the kinesthetic haptic feedback than the visual feedback. Kinesthetic haptic feedback could be a substitute for visual feedback for BCI tasks in situations where visual feedback is not feasible, and more studies around the cortical activity would help to illuminate the underlying mechanisms.

We also investigated whether repeated runs of the BCI training with feedback could improve the BCI classification accuracy over time. No significant improvement in the classification accuracy across 12 BCI runs was found in the visual feedback or the kinesthetic haptic feedback conditions, though a small positive linear trend for the BCI classification accuracy was observed for both feedback conditions. In BCI research, users have undergone repeated training sessions from a few days to several months in order to familiarize them with BCI control (Jeunet et al., 2016; Pfurtscheller, Neuper, Guger, Harkam, Ramoser, Schlogl, et al., 2000). The 12 BCI runs in this study may not have been enough to see a significant improvement in terms of the accuracy. Longer-term BCI training needs to be examined in future projects.

Three types of brain patterns were seen from the participants: 1) a power decrease in the alpha frequency band (8Hz to 13 Hz) during MOVE, 2) a power increase in the beta frequency band (13 Hz to 26 Hz) during MOVE, and 3) a small power difference between MOVE and REST. Brain patterns vary depending on the person and cannot be generalized, but in this study the participants who had clear power differences in the brain patterns (i.e. Type 1 and Type 2) had higher BCI classification accuracy than those with Type 3; Classification accuracy ranged from 63.67 to 90.28% for visual feedback, and 77.08 to 78.83% for kinesthetic feedback for Type 1 responders, it ranged from 56.56 to 81.17% for visual feedback, and 68.54 to 93.83% for kinesthetic feedback for Type 2 responders, whereas it only ranged from 53.58 to 60.71% for visual feedback, and 55.78 to 65.54% for kinesthetic feedback for Type 3 responders.

For the adult with physical impairments, unique brain activities were observed. The peak frequency of her response in both feedback conditions was at 13.5 Hz, which is within the range of beta frequency band, however, the power decreased during MOVE. From such a behaviour, this should be considered an ERD response, i.e., Type 1. This peak ERD response frequency was higher than that of all other participants without impairments, however, her brain pattern was repetitive, and as long as the BCI classifier is uniquely designed for each individual, reliable BCI performance can be achieved even with people who have unique brain patterns. Her average BCI classification accuracy was 66.5% for kinesthetic and 60.3% for visual feedback, and the highest was 72% for kinesthetic and 63% for visual.

Even though the participants had different visual perception set ups for the tasks in Chapter 5 and 6, the results of both studies indicated that the kinesthetic haptic feedback was effective for improving the BCI accuracy. In Chapter 5, when the kinesthetic haptic feedback was tested during BCI training, a blank screen was presented to the participants, so they had no visual feedback during the motor imagery tasks. On the other hand, for the task of Chapter 6, when the feedback was provided while using motor imagery to move the robot, the participants could see the consequences of the robot though no visual feedback on a screen was not provided. The kinesthetic haptic feedback resulted in significantly higher BCI classification accuracy than visual feedback, based on paired-samples t-test, in the case of Chapter 5 or higher BCI classification accuracy than no feedback, based on descriptive analysis, in the case of Chapter 6.

7.3 The Different Tasks and Robotic Systems

The eye tracking system and the BCI system were implemented in two different functional tasks, using different robotic systems. In Chapter 4, a teleoperation system was used in an object sorting task. In this system, eye gaze was used to determine the user's intended target, which generated the location of force guidance of the robot interface to help the users to traverse the correct path towards the target. This implementation was an improvement over the system in Sakamaki, Adams, Gomez, et al. (2017), where the force was created based on object recognition using computer vision and the system never allowed the users to make mistakes. The system in Chapter 4 allows the participants to select the target of their own choice using their gaze. The results showed that the auditory or vibrotactile feedback improved the performance of the gaze interaction. The force guidance did not improve the movement efficiency of adults without impairments; however, it did improve the movement efficiency for the adult and child with physical impairments. This implies that the force guidance was helpful for the users who had some limitations to their movements, but for users without impairments, the force was not necessary to perform efficient robot operation.

In Chapter 6, a mobile robot was used to knock over blocks. The eye gaze and BCI systems were combined to make an integrated human-robot interface. The eye tracker was used for detecting a target or destination of the robot in the environment, and the BCI was used for driving the robot towards the target. The interface also provided vibrotactile haptic feedback to help the users to fixate the gaze on a target object, and kinesthetic haptic feedback passively moving the hand in the same direction of the robot motion through the interface. A study of Frisoli et al. (2012), who developed an eye gaze and BCI driven controller of an exoskeleton for stroke rehabilitation in reaching exercises, took a similar approach but a head mounted eye tracker was used for target selection in physical environment and the exoskeleton facilitated the user's arm movement towards the target based on the movement intention. In that system, the user's arm was moved as the exoskeleton moved. Therefore, the system worked as kinesthetic feedback, which was closing a loop between the user's brain and the movement. The feedback from the exoskeleton assisted the user's arm movement, however, no feedback was provided for assisting the gaze interaction.

7.4 Eye Gaze and BCI Integrated Human-Robot Interface

Some eye gaze and BCI integrated interfaces have been studied in previous research, but many of them were designed for on-screen applications. Those integrated interfaces were for the control of devices such as a robot and a drone in the physical environment; however, they did not provide feedback to help the user to improve the control performance (Hwang et al., 2015; Kim, Kim, & Jo, 2014). The interface in Chapter 6 consisted of the eye tracking and the BCI system, where each system has a different role in robotic operation, and worked sequentially.

In Chapter 6, we examined the effectiveness of the feedback (i.e., vibrotactile haptic feedback for the target selection and kinesthetic haptic feedback for driving robot) for performing the functional robot task. The task with the haptic feedback was accomplished faster than without feedback for all the participants, with two participants showing a significant difference. For the target selection using eye gaze part of the task, no significant difference in time between the two feedback conditions was found. This result was expected because the target acceptance size for the gaze selection, a radius of 4.5 cm, was expected to be reasonably large enough for all the participants to select a target without timeout errors, according to the results of the Chapter 3. If more targets were placed in the task environment, the target acceptance size would need to be smaller in order to avoid false selections. In this case, the vibrotactile feedback would likely have had more impact on the performance of the target selection. For the portion of the task of driving the robot with motor imagery, the kinesthetic haptic feedback helped all the participants drive the robot and knock down the target blocks faster than without the feedback.

7.5 Mental Workload

Additionally, the NASA-TLX was used to measure the mental workload of the task and evaluate the systems in Chapter 5 and Chapter 6. All the participants, except one participant in

Chapter 6, reported that the task with the haptic feedback had less workload than the task without the haptic feedback. A higher workload overall was reported by the participants with physical impairments than the adult participants without impairments in both conditions, however, the score difference between the two feedback conditions was larger for the participants with impairments than the participants without impairments. Thus, the haptic feedback could be helpful in reducing workload while performing the tasks for the both participant groups, but more effective for participants with impairments.

7.6 Limitations

There were limitations in this study and improvements of these interfaces are needed that should be addressed for future studies. First of all, due to the small sample size of the participants with physical impairments, the findings in these studies can serve only as preliminary data guiding further research.

Secondly, reliable and constant robot operation was difficult for the participant who had involuntary movement and difficulty keeping her body still during the tasks. For the gaze interaction, because the user's eye movement was captured by the stationary eye tracker, successful gaze interaction was only made when she could fixate the head position within the range of the eye detection. For the BCI, the muscle activities of the body movement led to artifacts and noise in the EEG signals that affected the accuracy of the BCI classification. If such noise interferes with the EEG signals, it is difficult to detect the brain activities related to movement intention correctly, regardless of which filters and classification methods are used. In conventional EEG research, such noise and artifacts are removed offline, often manually, however, for the application of robot control, the EEG signal conditioning needs to be done on-line and the system requires processing the signals in real-time. Despite using temporal and spatial filters, those noise and artifacts tended to remain in the EEG, and it resulted in the lower BCI classification accuracy.

Lastly, the BCI tasks require the ability to maintain focused attention during the trial, and the long BCI sessions often made users feel tired. The lack of concentration and focus during the BCI trials can negatively affect a user's BCI performance. Therefore, it is crucial to find a way to maintain the participants' concentration and focus during the trials for BCI use. To address this, in the second study of Chapter 5 with the child and the adult with physical impairments, in order to make the BCI task more motivating and sustain their attention, the system was modified to a game-like activity. The session was generally one hour long, including the system setup and experiments; however, this session time may have been be too long for the child and the adult with physical impairments, according to the comments from the participants. It usually takes 20 minutes to put the EEG cap on a participant, and each session (i.e., classifier training or online run) takes about 2 and a half minutes. Therefore, one classifier training and two online runs can be conducted in a 30 minutes session. No more than 30 minutes per session would be a better session length for this population group.

7.7 Future Directions

It will be necessary to validate the proposed system with more children with physical impairments, our target population, to understand how the system could be effective and beneficial in their robot operations.

To better attain reliable and constant robot operation, some technical innovations should be implemented. For the eye gaze system to better handle head position movements, an accelerometer or inertial measurement unit (IMU) could be used to detect the head position and compensate for the head movement for the eye gaze position (Al-Rahayfeh & Faezipour, 2015; Linn et al., 2014). In addition, it is not reasonable to ask people with involuntary movement to stay still to avoid the BCI artifacts during robot control, thus, possible countermeasures are needed. For example, the control sequence of the BCI system could be modified such that when an artifact is detected, the system ceases to classify the signal and the robot ceases to move until the EEG signals are stable again. In our system, EEG signals were processed with the CSP spatial filter and classified with the LDA algorithm, which are said to be a gold standard method used in the BCI (Lotte et al., 2018). Different classification algorithms, for example, adaptive classification or Riemannian geometry classification method which are more robust to external disturbance, could be used to overcome the issue of the noise and artifact during on-line use(Gaur, Pachori, Wang, & Prasad, 2018; Lotte et al., 2018).

For some people who have severe physical impairments, the kinesthetic haptic feedback for motor imagery may not be feasible due to arm stiffness preventing them from holding the interface. Alternatives to the kinesthetic haptic feedback should be explored for such cases, such as vibrotactile haptic feedback. There is some research examining vibrotactile feedback for motor imagery-based BCI tasks. For example, Chatterjee et al. (2007) studied the effects of vibrotactile feedback provided to either user's left or right arm for the BCI classification between left and right hand motor imagery and found that the vibrotactile feedback improved the accuracy of the BCI classification over the no feedback condition. Our interface required the classification between MOVE and REST, thus, further research is needed to fully understand the effects of the vibrotactile haptic feedback in order for it to be applied with our system.

7.8 Conclusions

This dissertation demonstrated that the stationary eye tracker, the BCI, and combination of the two interfaces allowed users to directly interact with an object or robot in the physical environment, without the need for a computer display. In addition, biofeedback modalities, such as auditory, vibrotactile, and kinesthetic haptic feedback, added to those interfaces improved the participant's control over the gaze and brain activity, and thus enhance their performance of robot operations. For the eye gaze interaction, auditory or vibrotactile haptic feedback for the gaze fixation helped in target selection in the physical environment, especially for people who had physically impairments. For the BCI, use of kinesthetic haptic feedback improved the BCI classification accuracy compared to the visual feedback on a computer display. As the final system of the project, the eye gaze and BCI-based human-robot interface were integrated. The participants with and without physical impairments successfully demonstrated robot control with the integrated interface, and also showed the improvement of the task performance and reported less mental workload when the haptic feedback was provided.

It is also important to mention that the integrated human-robot interface in this study was developed with a low-cost consumer eye tracker, BCI, and haptic robot interface. Typical equipment used for eye gaze and BCI research for robot control are generally high quality expensive systems, however, those are not affordable for many people who may need the systems. This equipment would generally cost at least ten times as much as the total cost of our system. The eye tracker, BCI, and haptic robot interface, were only several hundred dollars each to purchase. Our proposed interface should be substantially more affordable than the equipment reported in those studies. The development of this proposed system could be a step towards the practical use of the eye gaze and BCI integrated interface in homes and in hospitals.

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