Preliminary Testing of a Telerobotic Haptic System and Analysis of Visual Attention during a Playful Activity

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Abstract— **Children with physical impairments face great challenges to play because of their limitations, for example, in reaching and grasping objects. Children with physical impairments can improve their independence, cognitive, and social skills by playing using robots. In this study, we developed a telerobotic haptic system with two haptic robots, one that is for a child and the other to interact with the environment. The goal of this study was to do preliminary tests of the haptic guidance method and the prediction of targets. Another goal was to explore and analyze the visual attention of the participants during the activity when eye-hand discoordination was induced. Five adults without disabilities played a whack-a-mole game using the robotic system, to assure that the robot works adequately before children with disabilities use it. The robots were programmed to induce eye-hand discoordination, so that haptic guidance would be required. A multi-layer perceptron neural network was implemented to predict the target moles that the participants had to reach, which in future versions, will control the activation of forbidden region virtual fixtures (FRVF) to guide the user towards the target moles. Analysis of participant's eye gaze led to the hypothesis that the less control a person has over the teleoperation system, the less they will look at the target. On average, the accuracy of the target prediction by the neural network was 70.7%. The predicting of targets will allow the robot to assist children during movement of the robot towards the target toy, without needing the children to explicitly point out with their gaze which toy they want to reach. This will potentially lead to a more intuitive and faster human-robot interaction.**

I. Introduction

The manipulation and interaction with toys during play activities have a great impact on the development of sensory, cognitive, motor, social and communication skills of children [1]. Play is a fundamental right that must be granted and promoted to every child and is one of the most important activities during childhood [2], [3]. Play involves discovery, mastery, learning, self-expression, and adaptation [4]. Through play, children develop rules about their own temporal and spatial locations and gain information about object properties [5].

Children with physical impairments such as cerebral palsy may have difficulties interacting with the environment and manipulating, reaching and grasping objects. Children with physical impairments have fewer opportunities to explore in play, compromising the learning of skills [6], [7]. Additionally, adults and playmates oftentimes are the ones who manipulate the toys, thereby children with physical impairments become the spectators rather than active participants in the play activities [8].

Previous studies have shown that assistive technology robots such as the IROMEC, the playROB and the Lego robots can be used to support play in children with disabilities [7], [9]. Results from these studies showed that children had fun and were the main protagonists of the pay activities. Additionally, it was demonstrated that robots could promote and increase engagement in play, improving learning skills and social participation in children with disabilities [10]. However, these robots only allowed children to see and hear what the robot was doing to their toys. No feedback of the physical information about the interaction of the robot with the toys was provided to children.

Robotic systems that use haptic feedback can transmit vibration or forces to provide the user with a sense of touch [11], [12]. Haptic interfaces can also implement guidance to help users do manual tasks with better performance such as lower completion times and higher success rates [13]. One form of guidance is the use of forbidden region virtual fixtures (FRVF). FRVF are software-generated forces that restrict the robot to be inside or outside a defined space [14]. FRVF have been implemented to support playful activities such as sorting of objects [15] and coloring tasks [16]. The user's eye gaze could inform the haptic guidance about the user's movement intentions.

The eyes can provide information about our intentions, emotional and mental states, and where our attention is focused [17]. Eye tracking systems can estimate the point of gaze (POG, i.e. the location where the person's gaze is focused). Different robots have been controlled with the user's eye gaze. A common approach is using the POG as a pointer on a computer screen showing buttons that command the robot to move. The robots controlled this way include Lego robots [18], drones [19], and wheelchairs [20], [21]. Also, a robot was controlled to guide the user's hand to the 3D point in the environment where the user fixated [22]. However, this approach presents several difficulties and limitations such as the Midas Touch problem, which is distinguishing from intended and unintended selection of targets. Also, it can be cognitive demanding for children. Children are required to constantly shift their gaze to the computer screen to make the robot move and look back at the robot to see the effect of their action [23]. In addition, the interaction with the robot and the environment can be slow.

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The present study is part of a project that aims to create a telerobotic haptic system for children with physical disabilities. The system is intended to provide children with the means to interact with their toys at a distance, e.g. from their wheelchair. The system will be guided with the children's POG and hand movements performed on the haptic user interface. The robotic system will analyze the children's POG to predict which target toy the child wants to reach before they reach it. And once predicted, we could assist the child during their movement to the target toy by applying haptic guidance. The advantage of predicting the targets over using the POG as a pointer is the freedom given to the child. Children can naturally gaze around the environment, rather than explicitly pointing out with their gaze which toy they want to reach using the robot. We expect that the human-robot interaction would be more intuitive and faster.

There are three objectives of this paper. The first one is to do a preliminary test of a telerobotic haptic system and its guidance method. The system implemented haptic guidance based on FRVF to guide the user in a whack-a-mole game, but at this stage the target mole position is known to the system, so that a neural network can be trained to predict the targets. To evaluate the robotic system, eye-hand discoordination is induced to make the non-disabled users do involuntary movements. The performance measures of time and length of the trajectories are used to evaluate the guidance method. The second objective is to explore and analyze the user's visual attention when using the telerobotic system to do the activity. The third objective is to test the performance of a multilayer-perceptron (MLP) neural network, which will control the activation of the guidance towards the target toys in future versions of the system. This algorithm was found to be the best at predicting targets in a previous research study [24]. In the previous study, we compared four different algorithms to predict the target blocks that users wanted to reach in a three-block task. In the present study, we analyze the accuracy of the predictions and discuss the potential risks if haptic guidance was applied according to the predicted output of the MLP.

II. Methods

A. System Description

The overall system consisted of two subsystems. The main subsystem included two PHANToM Premium 1.5A haptic robots (3D Systems, Inc., Rock Hill, SC, USA). One was placed in the environment (slave side) and the other in the user side (master side), for participants to control. The robots were programmed in bilateral teleoperation mode using a PID controller for position control. Hence, the two robots followed each other's position (e.g., if the user-side robot moved 2 cm in the x-axis, then the environment-robot did the same). This allowed the user to have haptic feedback, i.e. feeling forces implemented at the user-side robot when the environment-side robot touched an object. The robots were programmed in R2016a Matlab/Simulink and using the Quarc V2.2 library (Quanser Inc., Markham, ON, Canada) on a Windows PC. This library provides the necessary Simulink blocks for accessing external robotic devices such as the PHANToM Premium.

The second subsystem included a low cost Tobii EyeX eye tracking system (Tobii Technology, Stockholm, Sweden), and a LogiTech webcam (Logitech International S.A., Romanel-sur-Morges, Switzerland). The Tobii EyeX is a binocular eye tracker intended for gaming. It provides estimation in real time of the point of gaze (POG), with an operating distance of 540-800 mm, and has a nominal sampling rate of 55 Hz when controlled with the Matlab toolkit [25]. Gibaldi et al. [25] stated that this gaming eye tracker can be used in research applications in which fixation parameters, saccadic and vergence eye movements, and smooth pursuit are needed. Another Windows PC and the R2016b version of Matlab software were used to acquire the signals from the eye tracker and the webcam. A simple code was written in Matlab to record the user's eye gaze and the video of the trials at a sampling rate of 16z. The sampling frequency was lower than the nominal due to the integration of the webcam and the eye tracker. Additionally, at the start of the trials, the program sent a signal to the robots' PC, which facilitated the synchronization of the data collected from both subsystems. Communication between the two computers was done using user datagram protocol (UDP).

For the activity, a Whack-A-Mole Arcade Game by Fisher-Price was utilized. The game consisted of five moles with LEDs and switch-buttons to measure when the player whacked the mole. The game was adapted with a microcontroller, an Arduino Leonardo, to light up the LEDs and measure when the moles were pressed. The microcontroller also communicated in real time with the robot's PC using serial communication. For synchronization purposes, the robot's PC sent to the microcontroller which mole to light up. The target moles were randomly generated but predefined before the session. Also, the microcontroller sent to the robot's PC in real time the moles that were pressed.

B. Haptic Guidance

The haptic guidance was based on FRVF, which were implemented to help the users reach the target moles. The FRVF had a spherical shape that kept the user inside the space. The radius of the sphere decreased as the user got closer to the target mole, preventing the user from getting away from the target. The radius was determined as the minimum distance between the position of the environment-side robot and the target mole, analyzed in a two-second window, plus 0.5cm. The 0.5cm was added so that the user did not feel like he/she was up against the FRVF all the time. Once the target mole changed, the initial radius was re-calculated with the current distance between the end-effector and the target mole. The center of the sphere was the target. Fig. 1 illustrates the guidance method. This design is based on the findings in a previous study [15]. In that study, a person with cerebral palsy tested the FRVF in a sorting task. The shape was a cylinder that went from the pick-up location to the drop-off location. Results indicated that the motion of the person with physical disabilities was not a straight line, instead the person did arc-like movements. Therefore, the FRVF opposed the natural and preferred motion. The proposed spherical FRVF in this study would allow the person to move with more freedom, except for not letting him/her move away from the target.

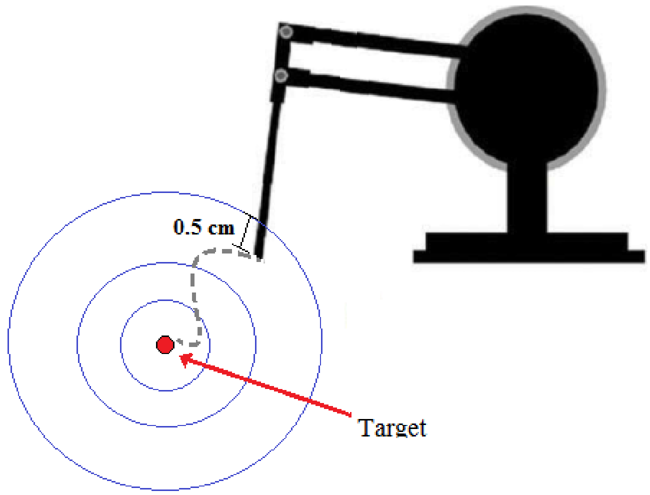

Fig. 1. Illustration of the FRVF as guidance method. As the user gets closer to the target, the radius of the sphere-shaped FRVF decreases, preventing the user from moving away from the target.

Additionally, four FRVF were implemented as spheres with 4cm of radius, which surrounded the moles that were not lit up. In this case, the FRVF were used to keep the user outside that space and prevent him/her from whacking the wrong moles.

C. Procedure

Five adults without physical or visual disabilities, four females and one male, participated in the study. One of them wore glasses. Ethical approval was obtained from the Health Research Ethics Board – Health Panel at the University of Alberta.

The playful activity was carried out with three different robot conditions: typical teleoperation, inverted teleoperation, and inverted teleoperation with guidance. Typical teleoperation refers to the robots following each other's positions. "Inverted" teleoperation was done with the purpose of inducing eye-hand discoordination in the participants, so that they made involuntary movements. Inverted teleoperation refers to inverting the x and y-axis of the teleoperation, and mirroring the z-axis. The environment-side robot moved in the x-axis according to the user-side robot's position in the y-axis, and in the y-axis according to the user-side robot's position in the x-axis. Also, when the user-side robot went upwards (z-axis) the environment-side robot moved downwards. Finally, inverted teleoperation with guidance refers to having the robots with inverted-axis teleoperation, but with the haptic guidance.

The order of the starting conditions was randomized. Three participants started with inverted teleoperation without guidance, and two started with guidance. This was intended to control for the learning effect. All participants played last using the robots with typical teleoperation, which served as control for comparing the results of the other two conditions.

Participants were asked to sit in front of the play area and rest their chin on a mounting arm, this was to record reliable data for the analysis of the visual attention and avoid recalibration due to head movements. In each robot condition, the participants played the whack-a-mole game until whacking a total of 60 moles. The moles were lit up one at a time, randomly, and without being repeated consecutively. After the mole was whacked, the next one was lit up. Participants were instructed to keep focus on the play area the entire time. Fig. 2 depicts the setup of the activity and the robotic system.

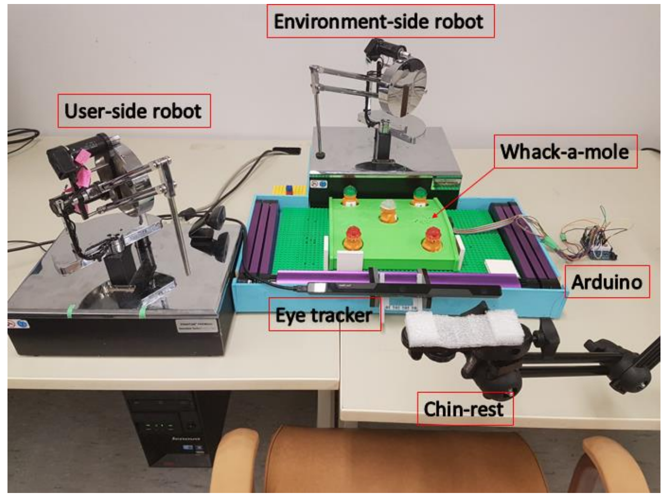

Fig. 2. Set up for the whack-a-mole activity game.

D. Data Collection and analysis

From each participant, the x, y, and z position of the environment-side robot, the eye gaze data, the moles that were whacked, and a video of the play area were recorded at 16 Hz. The data was processed to compose a dataset of 900 episodes. An episode consisted from the time the target mole was lit up until it was whacked. The final dataset was composed of 888 episodes, after excluding the episodes where the eye gaze was not detected (12).

During each condition, the time and trajectory length that the participants took to do the activity was measured. Additionally, the percentage of the episode period that the participants' eye gaze was on the target mole was measured. To compare the three conditions, the average of the measures was utilized. Also, the learning curve of each variable was plotted to visualize the improvements of the participants as the activity continued.

E. Neural network: Target prediction

The MLP was used to predict the target (mole) the user was supposed to go to. The MLP was implemented as a classifier. The input variables were seven: the x, y and z coordinates of the environment-side robot, and the x and y coordinates of the POG of the left and right eyes of the user. Windows of 4 (0.25s), 8 (0.5s), 12 (0.75s), and 16 (1s) samples were created to train the four neural networks. The datasets were created using the actual time (t), and inputs for past times (t – windows size). The size of the input layer of the network changed according to the windows size: N=window size*input variables. The output labels were the target mole that was lit up for each episode. The structures of the MLPs (N-M-O) were 28-20-5, 56-56-5, 84-70-5, and 112-80-5, for the window sizes of 4, 8, 12, and 16 samples, respectively. Fig. 3 shows the structure of the MLP neural network that was used in this study. Gradient descent was applied with a learning rate of 0.01 for the training.

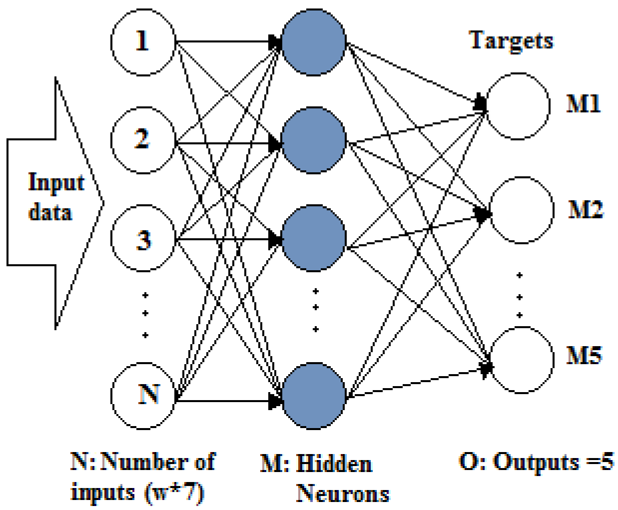

Fig. 3. Structure of the fully connected multi-layer perceptron neural network used for target prediction. The input data was the x,y,z coordinates of the environment-side robot end-effector, and the x,y coordinates of each eye. Window sizes (w) of 4, 8, 12 or 16 samples of the input data were tested. The output layer had five output neurons, one for each mole.

To train the MLPs, four datasets of 77854, 75725, 71583, and 70099 training examples were composed to train the MLP of 4, 8, 12, and 16 samples, respectively. The datasets contained the data from all three conditions. The purpose was to train the MLP with a high variety of movements. The MLPs were trained offline using 80%, and tested with the remaining 20% of the respective datasets. The accuracy was measured in four episode-intervals, only in the testing sets. Interval 1 had the data of only the first 50% of each episode. Interval 2 had the data from the 25% until the 75% of each episode. Interval 3 had the data from the 50% until the 100% of each episode. Interval 4 was the entire episode. To explore the stability of predictions, the average number of fluctuations in the prediction signal was measured for the episodes in the testing set. Results with the four different window sizes were compared, to find out the best window size that would lead to better predictions of the target mole the users were supposed to whack.

III. RESULTS

All participants played the game successfully. They had 100% success in whacking the correct moles with the three robot conditions. Table I presents the average time spent by the participants to complete the activity, and, the average trajectory length traveled by the participants. Finally, Table I lists the average percentage of visual attention that participants devoted to the target mole.

Participants had great difficulties to control the environment-side robot with inverted teleoperation, having the x and y axis inverted and the z axis mirrored. The most challenging was understanding that if the user-side robot moved to the right, the environment-side robot would move towards the front. For this reason, they spent more than three times the time spent with typical teleoperation, and travelled more than twice the distance.

TABLE I. AVERAGE PERFORMANCE IN THE WHACK-A-MOLE GAME WITH THE THREE ROBOT CONDITIONS

	Time (min)	**Trajectory Length (m)**	**Visual attention on the target (%)**
Typical	2.34±0.46	15.68±2.09	61.01±22.72
Inverted with Guidance	9.07±5.43	40.65±21.56	43.22±22.89
Inverted with no Guidance	8.84±3.36	36.67±9.12	44.10±21.56

The variance of the results is because three participants started with inverted teleoperation and without guidance, while two participants started with guidance. The three participants that started without haptic guidance had lower times and trajectory lengths in the second trial when they played the game with guidance. In contrast, the participants that started with haptic guidance had better results in the second trial, without haptic guidance. In terms of the percentage of visual attention on the target, this measure was similar for trials with and without the haptic guidance.

Fig. 4 depicts the learning curve in terms of time spent in whacking each mole for the participant with the scores closest to the average. This participant started with inverted teleoperation with haptic guidance. A similar behavior was observed in terms of trajectory length. However, a trend was not observed in terms of percentage of visual attention on the target mole, therefore it was not drawn.

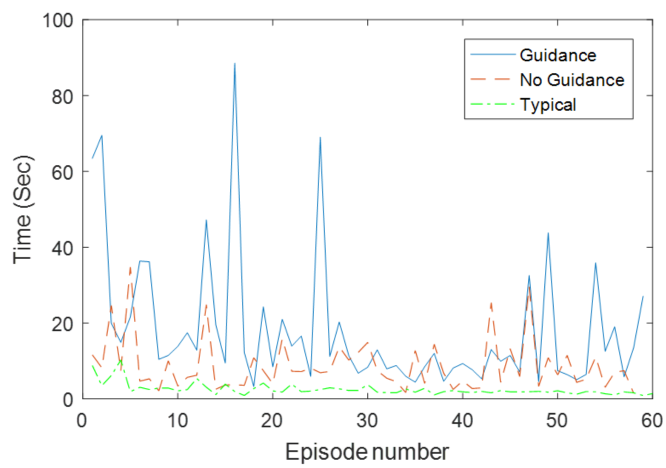

Fig. 4. Learning curve of the participant with scores closest to the average.

Table II lists the accuracy of the MLPs predictions with the different window sizes. The accuracy is reported for each of the intervals of the episode, and for the complete episode.

TABLE II. ACCURACY OF THE TARGET PREDICTIONS FOR EACH WINDOW SIZE OF THE MLP NEURAL NETWORKS

Window size	**Accuracy (%)**			
	Interval 1	***Interval 2***	***Interval 3***	***Entire episode***
w=4	46.3	60.3	66.4	56.2
w=8	45.7	66.5	78.4	62.6
w=12	50.7	78.6	89.3	70.6
w=16	48.9	74.8	**90.2**	70.7

The average number of fluctuations (changes in the target prediction) per episode were 7.91, 5.42, 4.06, and 3.48, for the 4, 8, 12 and 16 sample windows, respectively.

IV. Discussion

As expected, the participants performed better with typical teleoperation compared to the other two conditions. The inversion served its purpose to confuse the able-bodied users and thus make demands on the guidance aspects of the robotic system. We had expected that the inverted results would be in favor of when haptic guidance was applied. The participants who started with guidance took longer than when they did the activity without guidance. A possible reason why the participants did not perform better with the haptic guidance is because the FRVF were designed only to restrict the user from moving away from the target and not actively guide (push) him/her towards it. It was observed that participants often followed the sphere walls without getting closer to the target.

In terms of visual attention, when participants had the inverted teleoperation, they fixated at the target mole around 44% of the duration of the episodes. The rest of the time, the users were mainly looking at the effector and the possible obstacles (the moles that were not lit up). By inverting and mirroring the axis, the participants' eye-hand coordination was diminished, thus making their movements less reliable. Therefore, they had to rely more on visual feedback from the environment-side robot's end-effector, compared to typical teleoperation. We had expected that the haptic guidance would help the users gain more control and improve their coordination. As the guidance method did not improve the user's performance in the activity, we will test this hypothesis in a future study using a different form of haptic guidance.

When people without disabilities move their hand to reach an object, their visual attention is on the target and never on the hand [26]. Studies about upper-limb artificial prosthesis users have found that during reaching and grasping tasks, skilled users fixate at the target object a higher percentage of the movement period compared to inexperienced users [27]. The lack of full proprioception feedback (i.e., awareness of the movement and position of the body parts) from the prosthesis requires the user to rely on visual feedback. In this study, participants fixated at the target mole less during the inverted teleoperation than in typical teleoperation, as they could not rely on the proprioception feedback provided by the haptic user-side robot. In a sense, the less control a person has over the telerobotic system, the less he/she will look at the target mole. More research is required to understand the visual behavior in children with physical disabilities when they use robots.

It was observed that users improved by spending less time and travelling less distance as the activity progressed (e.g., Fig. 4 for one participant's time). This behavior was not observed for the visual attention data. However, if participants had more time to use the robot, we would expect their visual attention on the target to increase. This will reflect their skill level at controlling the robot, as happens with prosthetics users [27].

Regarding the prediction of targets, from Table II it is possible to observe that the performance increases with the increase of the window size. Accuracy increases and the average number of fluctuations decreases with the window size. This is because with a bigger window size the input for the MLP increases, thus providing more information leading to more accurate predictions. Additionally, higher accuracy was achieved when the MLP was tested using the last part of the episodes (interval 3). This means that the MLP had a better accuracy when participants were approaching the target. The lowest accuracy was obtained in the first half of the episodes (interval 1), On average, the performance of the MLP of 16 samples was lower than in our previous study, where the MLP achieved 94% [24]. Possible reasons are that in the whack-a-mole game there were more targets, the participants were not asked to move back to a starting position, and eye-hand discoordination was induced.

The MLP did not provide stable predictions throughout the episodes. With a window of 16 samples the MLP had the fewest fluctuations (3.48). However, if haptic guidance was applied towards the targets predicted by the MLP, haptic forces would be applied rapidly in different directions based on fluctuations towards different targets making the user uncomfortable or causing the teleoperation to be unstable. Using FRVF guidance has less instability issues in the teleoperation system than if we applied attraction forces towards the target. In case that the prediction of the MLP fluctuates to wrong targets, the FRVF would not allow the user to go to their desired target but it would not pull them towards the wrong target, which has more potential of causing instability in the teleoperation system.

In this study, the data of the five participants in the three robot conditions were grouped together. In other words, we tested the one-size-fits-all approach. Perhaps the MLP could perform better if it was trained specifically for each person, or for each robot condition. However, this would require a bigger dataset from each person, therefore, the person would need to play more using the robotic system. Also, the MLP would need to be trained differently if the toys are not static and if the users can move their heads freely.

For future work we will improve the haptic guidance by implementing the FRVF in a cone shape or potential force fields, so that better performance can be achieved. Also, the system will be evaluated with the haptic guidance being directed by the output of the neural network. We will explore different options to improve the performance of the MLP neural network for predicting targets, including training a neural network for each person and for each condition, and including more input variables. Also, the best strategy will be identified to apply the haptic guidance in case the MLP does not reach 100% accuracy. In the upcoming stage of the project, we will be testing the system with adults and children without disabilities. We can gain insight about the possible demands of the system and take them into account for subsequent trials by children with physical disabilities.

V. Conclusions

Telerobotic systems could help children with physical disabilities to play if they have difficulties reaching their toys. The user-side robot could be mounted on the child's wheelchair, for example, thus increasing the opportunities to interact with their world.

In this study, five adults without disabilities tried a telerobotic haptic system to play a whack-a-mole game. Inverting the axis of the teleoperation system induced eye-hand discoordination in the participants, which allowed us to test the FRVF guidance. The haptic guidance that was implemented in this study did not improve the performance of the participants. The FRVF prevented the participants from getting further away but did not help them to get closer. The guidance needs to be more active so that it can guide the users towards the targets easier and faster.

In terms of visual attention, participants had their eye gaze on the target longer in typical teleoperation than in inverted teleoperation. The proprioception feedback from the haptic interface was confusing, hence the users had to rely more on visual feedback while watching the environment-side robot's end effector and other moles. We hypothesize that the less control a person has over the teleoperation system, the less they will look at the target. However, these results are exploratory and cannot be generalized, more research required.

The user's eye gaze and the environment-side robot's position can be used for the prediction of target toys that the user wants to reach. We implemented and compared four MLP neural networks with inputs of window sizes of 0.25, 0.5, 0.75, and 1s. The MLP with a window size of 1s performed the best in the whack-a-mole game. The accuracy for prediction of targets increased as the robot end effector got closer to the target mole. On average, the MLP had a 70.7% accuracy throughout the testing episodes. This accuracy may cause a robotic system to be unstable if haptic guidance was applied with the network's output. Also, as the guidance affects the movements of the users, this may affect the MLP's performance. For future work, before testing the MLP and the guidance together, we will improve the accuracy by including more input variables such as velocity and direction of the robot during the tasks.

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