Design and Preliminary Evaluation of an Augmented Reality Interface Control System for a Robotic Arm

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ABSTRACT

Despite advances in the capabilities of robotic limbs, their clinical use by patients with motor disabilities is limited because of inadequate levels of user control. Our Johns Hopkins University Applied Physics Laboratory (APL) team and collaborators designed an augmented reality (AR) control interface that accepts multiple levels of user inputs to a robotic limb using noninvasive eye tracking technology to enhance user control. Our system enables either direct control over 3-D endpoint, gripper orientation, and aperture or supervisory control over several common tasks leveraging computer vision and intelligent route-planning algorithms. This system enables automation of several high-frequency movements (e.g., grabbing an object) that are typically time consuming and require high degrees of precision. Supervisory control can increase movement accuracy and robustness while decreasing the demands on user inputs. We conducted a pilot study in which three subjects with Duchenne muscular dystrophy completed a pick-and-place motor task with the AR interface using both traditional direct and newer supervisory control strategies. The pilot study demonstrated the effectiveness of AR interfaces and the utility of supervisory control for reducing completion time and cognitive burden for certain necessary, repeatable prosthetic control tasks. Future goals include generalizing the supervisory control modes to a wider variety of objects and activities of daily living and integrating the capability into wearable headsets with mixed reality capabilities.

INTRODUCTION

Assistive robots are a type of personal service robots[1] used in the field of rehabilitative medicine to increase patients' functional independence through replacement of lost or impaired motor ability. In particular, advanced robotic prosthetic limbs and hands hold great potential as both assistive and restorative devices for individuals with paralysis, neuromuscular conditions, and neurodegenerative diseases. Wheelchair-mountable robotic arm systems are now available for these individuals, including the iArm (Exact Dynamics, Didan, the Netherlands). Although these robotic limbs are highly capable, control of prosthetic upper limbs has lagged behind the mechanical capabilities of the robotic systems themselves. This is especially true for users with paralysis, whose control is generally limited to low-bandwidth joystick, sip-and-puff, or brain–machine interface (BMI) outputs driving individual joints or robotic degrees of freedom (DOF).

Recent and ongoing advances in autonomous robotics, including computer vision sensing[2] and intelligent trajectory-planning algorithms,[3] hold extreme promise for improving assistive technology. To date, several studies have described efforts to add machine intelligence to assistive device control,[4,5] including intelligent wheelchairs for navigating crowded spaces or occluded paths,[6,7] intelligent robotic limbs,[8–11] and humanoid service robots that help disabled individuals perform household chores.[12] Visual feedback has been integral to these autonomous and semiautonomous systems to provide information to the user during planning and execution of preprogrammed movements. Augmented reality (AR) builds on this by providing computerized visual feedback overlaid on the natural environment with which the user is interacting, allowing for a more seamless integration into the user's daily living.

Because of underlying impaired functionality, the method of user interaction with semiautonomous systems is of critical importance. In this regard, eye movement tracking has demonstrated effectiveness in assistive communication devices,[13] as well as control of wheelchairs[14] and robotic limbs.[10,15,16] Eye tracking alone can suffer from issues such as the Midas touch problem of eye-tracking cursors making unintentional screen object selections[17] and technical limitations including control of systems with more than two DOF. These issues can be largely overcome via intuitive AR control interface design and the integration of machine intelligence into the robotic system.

BACKGROUND

Fully autonomous robots have made significant advances in the past few decades as evidenced by performance in the Defense Advanced Research Projects Agency (DARPA) driverless car[18] and robotics challenges.[19] These successes have relied on advancements in environmental sensors like computer vision sensing and image segmenting technology, as well as development of algorithms that allow the robot to operate in its data-rich environment. This technology has reached a maturation level such that autonomous robotic assistants are being developed as assistants to older users.[20] The use of full autonomy, however, limits the system to movements or actions that have been preprogrammed into or taught to the robotic system; this inherently constrains the ability of users to creatively overcome unforeseen obstacles or increase the number of tasks they attempt with the system. Additionally, in the case of individuals using robotic limbs, full autonomy may negatively impact embodiment of the limb by the user and, ultimately, the extent to which the limb is used. Control strategies that share control between users and the robotic system can combine benefits of both autonomous and direct control systems. A variety of strategies for augmenting direct control with machine intelligence have been demonstrated, including shared control,[8,21–23] supervisory control,[10,11] and adjustable autonomy.[24]

A semiautonomous system allows for supervisory control in which users indicate a high-level goal (e.g., "I want to eat that apple") to be carried out by a context-aware robot. In some instances, a multimodal control approach and interface can enable automation of a list of known actions (e.g., grabbing objects on a surface, bringing objects to a user's face), while still allowing completion of unanticipated novel tasks. Our group has developed a robotic system and interface that takes a variety of user input signals and enables supervisory control over a robotic upper limb. Previous pilot studies of the system have demonstrated effectiveness of supervisory control with hybrid invasive intracortical BMIs[10] and shared BMI control with eye tracking,[21] but the system itself has been modularized to allow for a number of inputs.[25] These previous versions included rudimentary visual feedback and relied on invasive brain control. The version developed for the present study uses noninvasive eye tracking to select between AR content and provide multimodal control (direct movements and supervised actions).

For this study, we designed and tested an AR control interface system that shares control between a wheelchair-bound user and a context-aware robotic system, with the goal of achieving functional object interactions through use of a robotic limb. The system uses an AR eye tracking interface on a user-facing monitor with an affixed eye-tracking sensor that allows users to either control each movement of the robotic limb (direct control) or select high-level goals via an AR menu (supervisory control). We performed a pilot study to assess how well the AR system worked in a cohort of three subjects with motor disabilities from Duchenne muscular dystrophy. The subjects attempted robotic control of an object pick-and-place task using both supervisory control of a robotic limb and traditional direct control. To demonstrate the flexibility of the direct control system, two subjects additionally attempted to perform a more difficult water-pouring task.

AR CONTROL INTERFACE DESIGN

The AR control system employs a modular framework leveraging computer vision and multimodal input signals to provide intelligent control over robotic upper limbs (Figure 1). The control system presented in this article extends previously reported computer vision, eye tracking, intelligent robotic control, and command integration system modules[25] by developing an all-inclusive

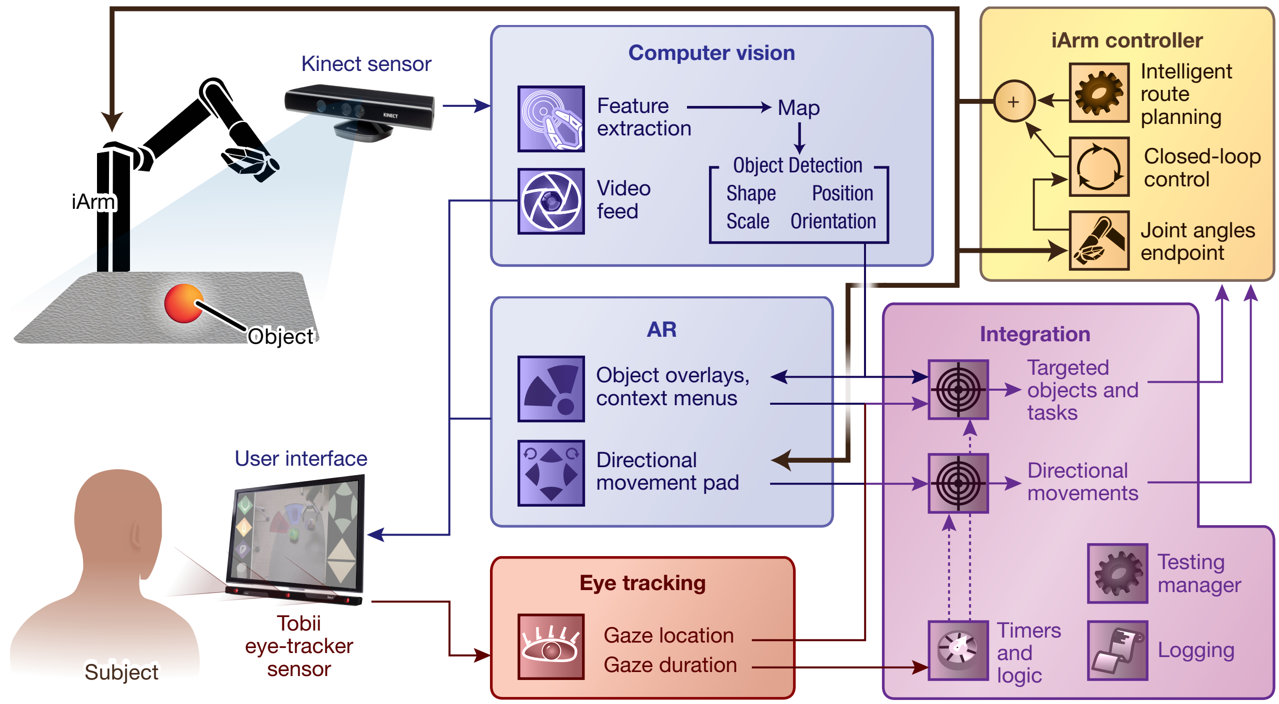

Figure 1. Experimental setup and block diagram of an eye-tracking-based supervisory control system with interactive AR. Control of the iArm system is accomplished through interaction with AR content linked to both continuous directional control and task- and object-based supervisory control modalities. The figure details several modules of the system, including computer vision, AR, eye tracking, and the integration and iArm controller modules that carry out the desired action.

AR interface command suite that can use eye tracking alone for control (Figure 2). A Robot Operating System (ROS) controller communicates with a graphical user interface (GUI) developed in the Unity (Unity Technologies, San Francisco, CA, USA) development environment via a 50-Hz user datagram protocol (UDP) message passing framework.

Herein we highlight the use of an eye-tracking-based control interface enabling subjects to interact with dynamic AR content. The interface and controller direct the iArm, a commercial assistive robotic manipulator, to complete simple pick-and-place actions. This single-object interaction task was selected to permit assessment of direct and supervisory-based control approaches through an AR-based control interface. Thus, for direct control the iArm was commanded through the interface using directional endpoint-based commands paired with direct joint-based commands to the end-effector gripper. For task-based supervisory control (e.g., picking up objects), users would select the task through the interface, and the iArm was sent dynamically programmed endpoint trajectory commands until task completion.

Eye Tracking Control Input

The subject's gaze position was tracked using a Tobii (Danderyd, Sweden) EyeX sensor mounted to the bottom of a monitor positioned in front of the subject. The Tobii EyeX software application programming interface (API) enables direct integration into the Unity environment, where the visual interface and AR content are displayed. Eye tracking allowed users to navigate dynamically generated AR content displayed on a monitor (Figure 2). Using a fourth-order running average filter, eye tracking fixation and gaze point localizer algorithms provided through the Tobii EyeX software development kit (SDK) were modified to smooth movement and avoid cursor jumping.

Computer Vision

A Microsoft (Redmond, WA) Kinect sensor was placed on a stand above the robotic system to scan the environment around the robotic system and identify targets for manipulation. Additionally, it provided a real-time red-green-blue (RGB) video broadcast of the work space, which was presented to the user on the monitor. Data collected from the Kinect was processed using the OpenNi camera (http://wiki.ros.org/openni_camera) package in ROS to identify object locations and features (e.g., size, shape) in the scene. Object information was sent at 50 Hz over UDP to both the robotic control system and the AR interface. This information enabled the generation of scaled AR content overlaid on objects in the RGB video broadcast. AR content positions were updated dynamically after co-registration with detected objects from the computer vision module. The AR content also possessed a limited object permanence capability, remaining in place for a set period of time or until re-registered by a subsequent object detection.

AR Interface

An interactive AR visual control interface was developed to support both direct real-time control and task-based supervisory control modes. This GUI provided the user with a live video broadcast of the work space around the robotic system and displayed interactive features and menu systems to allow selection of real-time commands to the robotic system (Figure 2). The Unity development platform enabled generation of both an interactive visual display and a 3-D model of the work space around the robotic system. Figure 2 shows sample screen captures of the live video broadcast with AR overlays.

Users are presented with a visual control interface consisting of three main panels (Figure 2), each with interactive content: (1) a left panel with grasping commands, (2) a center panel containing a visualization of the work space and robot with dynamic AR content for both lateral direction movement control or object-focused supervisory control of the robotic system, and (3) a right panel with out-of-plane endpoint and up-and-down movement controls. Grouping of interactive control content was designed to reduce the need for movement across multiple panels for common task subcomponents.

Interaction of the cursor position (controlled via eye tracking) with AR content was processed using a state controller that evaluated the current control mode of the system, the duration of interaction with specific AR content, and previous AR content interaction. Actions tied to AR content were initiated if the cursor position crossed the content's boundaries and remained for 100 ms, which was sufficient time to reduce the likelihood that movement of the cursor across the extent of content boundary would initiate undesired actions. If AR content associated with one type of control was selected, then AR content associated with other types of control would be removed temporarily from the screen. This mode switching is common with other conventional controls and is intended to reduce user errors for real-time device control.

Supervisory and Direct Control

Both supervisory and direct control strategies were implemented and tested in this study during a simple pick-and-place task. During direct control, the user continuously and serially adjusted the direction, orientation, and aperture of the gripper with an input interface similar to that of a virtual joystick. During supervisory control, the user initiated a preprogrammed action (i.e., autonomous grasping of the object) by selecting the

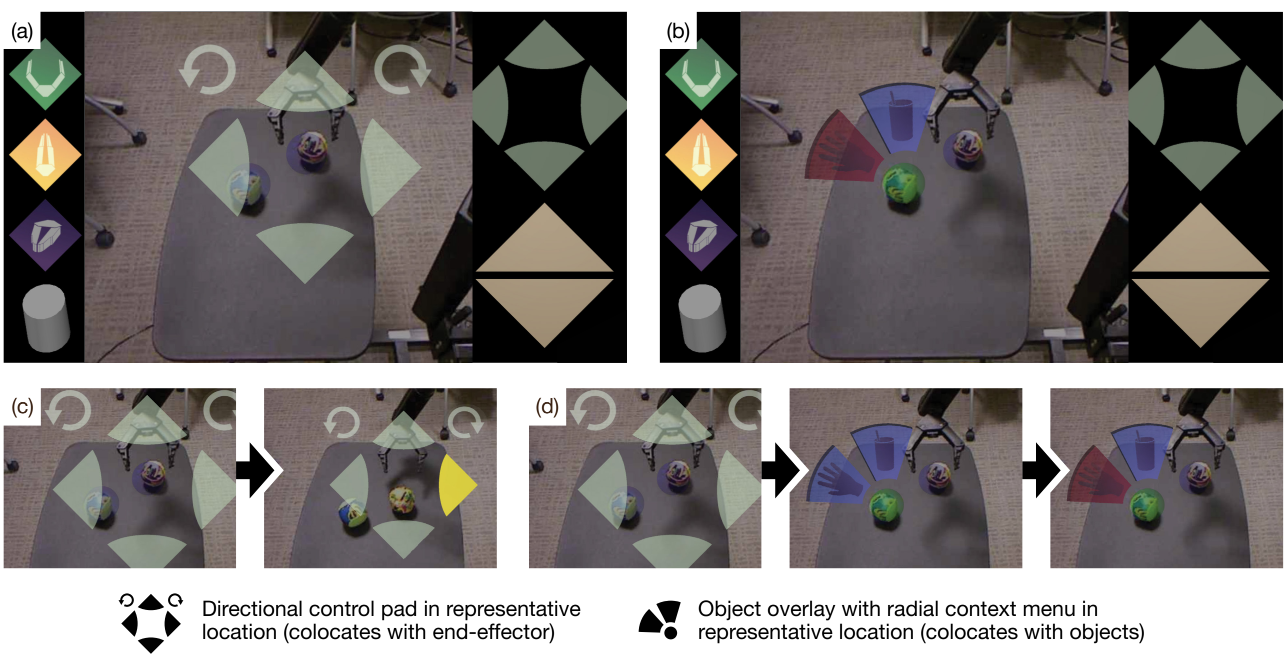

Figure 2. Screen shots of the AR visual control interface depicting the RGB video broadcast from the computer vision sensor and the layout, appearance, and various interactive states of AR content. (a) The default presentation of AR content, with the scenario showing two objects, the directional control pad dynamically colocated with the endpoint (or end-effector) of the iArm system, and AR object overlays dynamically scaled and colocated with objects detected by the computer vision. (b) Radial context menus for the selected object overlay, presenting supervisory control options with exemplars for grabbing an object (hand icon) and for grabbing and bringing a drink to the user (cup with straw icon). (c) The process flow for usage of the directional control pad depicting the temporary disappearance of AR object overlays for supervisory control mode. (d) The process flow for usage of AR object overlays depicting the presentation of the radial context menu and the temporary disappearance of the control pad for directional control mode.

corresponding AR content (Figure 2b). This command was executed to completion unless the user activated another AR content control feature, effectively canceling the previously selected autonomous action. The state controller managing the AR interface also determined what content was present and available for selection by the user. For example, the lateral direction controls would disappear after the presentation of radial context menus around selected objects.

The left and right panels, respectively, displayed static grasping and endpoint/orientation controls that were available to the user at all times. The left panel contained direct grasping controls for opening and closing the end-effector gripper (iArm gripper shown in green and yellow diamond-shaped "buttons") and for rapid reorientation of the end-effector for in-plane object manipulation (purple diamond) (Figure 2a). Interaction with these left-panel buttons directed velocity-based movement of the end-effector. The right panel contained buttons that provided additional real-time directional and orientation controls of the robotic system endpoint. The directional control for upward and downward (out-of-plane) movement was present in the bottom half of the panel for each clinical evaluation performed within the study.

The center panel displayed a real-time RGB video broadcast of the work space from the computer vision sensor, as well as semitransparent AR content controls for in-plane directional movement and semitransparent AR object overlays for object-focused task-based actions. The four-way directional controls maintained relative position around the robotic end-effector as its position changed, which limited the need for a user to displace their eye gaze during directional control.

During supervisory control, the center panel also depicted semitransparent AR overlays on detected objects (Figure 2d). Once an AR overlay was "selected" through cursor interaction, radial AR menus were presented that contained options for semiautonomous supervisory control of high-level tasks (e.g., grasp object, bring object to mouth). Similar to the directional controls, this AR content was positioned within the Unity virtual world representation, allowing both position and scaling relative to the object and screen.

PILOT STUDY

Methods

Three subjects were enrolled in a pilot study to test the AR eye tracking control interface. Subjects were aged 30–41 and all were diagnosed with Duchenne muscular dystrophy. All subjects relied on powered wheelchairs for mobility. No subjects had previous experience with or were currently using eye tracking assistive devices. This study was approved by the Johns Hopkins Hospital Institutional Review Board (NA_00093495).

Subjects were given an initial period to familiarize themselves with the system controls. At the onset of this familiarization period, eye tracking software was calibrated using the Tobii EyeX calibration software. After calibration, subjects were allowed to interact with the system to determine their comfort with layout, button functions, and eye tracking accuracy. Eye tracking was recalibrated at this time if necessary. Subjects progressed to the task performance and evaluation phase, which included roughly 1.5 hours of test protocols, at their discretion, leading to slightly differing numbers of completed test trials. Eye tracking was not recalibrated after entering the task performance and evaluation phase. A fourth subject, whose data is not included in this study and who was not diagnosed with muscular dystrophy, was unable to familiarize herself with the control system within her testing period.

The evaluation task tested a subject's ability to perform a pick-and-place task, where the iArm was driven from an initial resting position to grasp a ball on the table and deposit the ball at a target position across the length of the table. Participants were positioned facing the AR interface screen and eye tracker (Figure 1). The table with the attached iArm and object of interest was placed within the field of vision of the participant but required the participant to deviate their gaze from the screen and often turn their head for full visualization of the setup. As such, participants did have the opportunity to track their progress if desired through direct visualization of the setup. Study participants were given an on-screen prompt at the beginning of each trial. This prompt started the timer for the task. Task completion was manually documented when the ball was successfully placed at the end location and the grasper was no longer in contact with the ball. Subjects 1, 2, and 3 completed 7, 19, and 10 direct trials and 10, 20, and 15 supervised trials, respectively.

Two control methods were tested. Under the direct control method, the participant was directly responsible for all movements and grasps of the iArm through on-screen AR prompts for direction and grasp, as previously described in the control system description. For the supervisory control method, the user was allowed to select an on-screen AR button that automated movement of the iArm from its resting position through the grasping of the selected object. After any movement, the participant was then responsible for moving the ball to the final location. While operating the supervisory controller, the user could interrupt the automated movement by selecting any on-screen button. Of note, initial testing revealed a low threshold for the system to prematurely end automated movements, since it tended to capture users' inadvertent eye gazes. The threshold was subsequently altered between Subjects 1 and 2 to improve the usability of the system. To reduce the effect of training, the control method was switched at regular intervals (every four to six repetitions depending on user preference) during the experiment. When there was a change in the control method, the user was informed before the task started. (See the supplemental video at https://www.jhuapl.edu/Content/techdigest/videos/AR-control-robotic-arm.mp4).

Outcome Measures

The portion of the task analyzed for this pilot study was the phase ending with grasp of the object, since both supervisory and direct control trials used direct controls to place the object once grasped. The primary outcome measure compared was task completion time. Subjects were given as much time as necessary to complete the task. If outside assistance was needed, such as when the ball rolled off the table, completion time included any time taken to replace the ball within usable position. Additionally, all eye movements during the experiment were tracked during each task. Eye tracking information was used to calculate a path length of gaze on the screen. The eye tracker was sampled at an average of approximately 50 Hz and was resampled to exactly 50 Hz offline. These positions were then smoothed with a fifth-order moving average filter such that path length calculations were completed at an effective sampling rate of 10 Hz. Path length in this sense was calculated as the sum of the pixel distances between successive samples. Median completion times, path lengths, and number of off-screen saccades were compared across trials for each subject independently, using a nonparametric two-sided Wilcoxon rank sum test.

The eye tracker did not track eye movements that occurred off screen—off-screen positions were logged as the last on-screen position—so path lengths are conservative. To track saccades toward off-screen targets, on-screen eye position that was recorded as being at any combination of minimum or maximum position values (i.e., corresponding to the leftmost pixel of the screen or the topmost pixel of the screen) was assumed to be a part of an off-screen saccade.

Once trained and evaluated on direct and supervisory control strategies with the system, Subjects 2 and 3 were given the opportunity to attempt a water-pouring task. In this task, subjects used the system's direct control strategy to pour water from one cup into another cup. Analysis of the water-pouring task in this study is limited to a qualitative description, given the limited number of trials collected.

Table 1. Mean completion times

Subject	Direct (sec)	Supervisory (sec)	Improvement (%)	*p* (Wilcoxon test)
1	55	26	52	0.0046*
2	54	41	25	1.1e-4*
3	60	33	44	2.8e-4*

Table 2. Mean eye tracking path lengths

Subject	Direct (kilopixels)	Supervisory (kilopixels)	Improvement (%)	*p* (Wilcoxon test)
1	31	9	69	4.1e-4*
2	34	17	53	3.4e-7*
3	39	10	75	3.5e-5*

Results

Average grasp completion times differed significantly between direct and supervised methods for all participants ($p < 0.05$, Wilcoxon test). Completion times for each subject and control scheme are detailed in Table 1. Supervised control resulted in reduction in grasp completion times by 52%, 25%, and 44% in Subjects 1, 2, and 3, respectively. In two instances each for Subjects 2 and 3, the ball fell off the table with subjects' attempts at grasping. For Subject 2, both of these instances happened during direct control strategies. For Subject 3, one instance occurred during the direct control strategy and one occurred during the supervisory control strategy. For both subjects, the ball was immediately replaced at the start position and the subject was allowed to resume the movement from the current location of the iArm. These instances were included in calculating overall completion time averages.

On-screen path length for eye tracking also differed significantly between the trial modes for all participants ($p < 0.05$, Wilcoxon test). Path lengths for each subject and control scheme are detailed in Table 2. Supervisory control resulted in a 69%, 53%, and 75% reduction in path lengths for Subjects 1, 2, and 3, respectively. Path lengths are also shown in Figure 3 to demonstrate the quality of eye gaze paths for direct and supervisory control.

Saccade movements varied by user and control method. Off-screen saccades were greater for Subjects 2 and 3 ($p < 0.05$, Wilcoxon test) during the automated movements compared to direct control (Table 3).

Subjects 2 and 3 successfully performed the water-pouring task by means of direct control (Figure 4 and supplementary video). This required translating the gripper near the cup, opening the gripper, and closing the gripper around the cup with a delicate grip that would not crush the cup. Once the cup was grabbed, the cup in hand was translated to a precise spot above and near the target cup, and the gripper's wrist was rotated slowly toward the target cup until the water had been fully transferred.

Table 3. Mean off-screen saccades per trial

Subject	Direct	Supervisory	Change (%)	*p* (Wilcoxon test)
1	2.71	0.80	–70	0.36
2	3.47	7.15	+106	5.3e-4*
3	2.00	6.07	+204	4.8e-5*

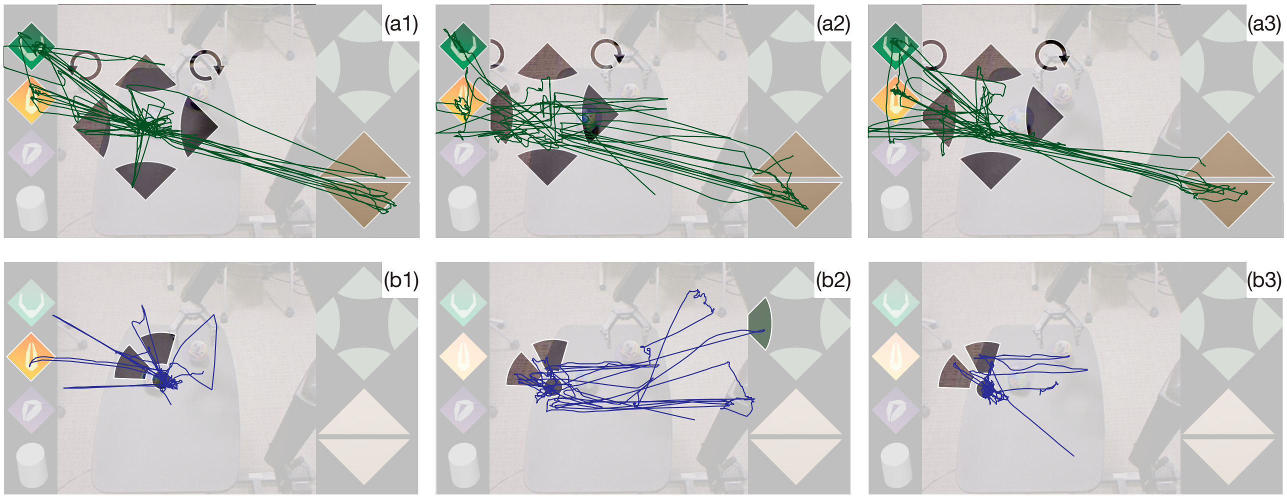

Figure 3. Eye tracking traces displayed on an overlay of the actual experimental monitor setup. The top row (a1–a3) shows the eye tracking traces for each of three subjects using direct control. The bottom row (b1–b3) shows the eye tracking traces for each of three subjects using supervisory control.

DISCUSSION

Our pilot study demonstrated the effectiveness of the AR system to allow users to control a robotic limb to perform a pick-and-place task using both supervisory and direct control strategies. The AR eye tracking control interface also demonstrated the potential of supervisory control, which enabled improvements over direct control in an initial grasping phase of the pick-and-place task. With the use of a supervisory control method, grasp times improved 25–52% from direct control ($p < 0.001$), while gaze path lengths decreased more than 50% in all subjects (Figure 3). Off-screen saccades during automated grasps increased in two of three participants, likely due to user desire to ensure the automated movement was progressing as expected through observing the arm movement directly rather than through the visualization on screen. The use of direct control for a more complex water-pouring task, though limited in the number of trials, demonstrated the generalizability of direct control systems to novel situations.

The modularity of the control system allows for rapid iteration and improvement. The AR interface and backend controller enabled users to employ either direct or supervisory control strategies, depending on task instructions or constraints. Previous versions of the control system relied on both eye tracking and neural signals from intracranial implants,[10,21] but this study demonstrates the viability of eye tracking alone. The noninvasive nature of eye tracking makes it a particularly attractive modality for potential users who favor it and other wireless assistive technologies.[26] The use of the iArm in this study also shows the modularity of the robotic limb controller, which was initially designed for the APL-developed Modular Prosthetic Limb (MPL).[27] The relative affordability of the iArm and

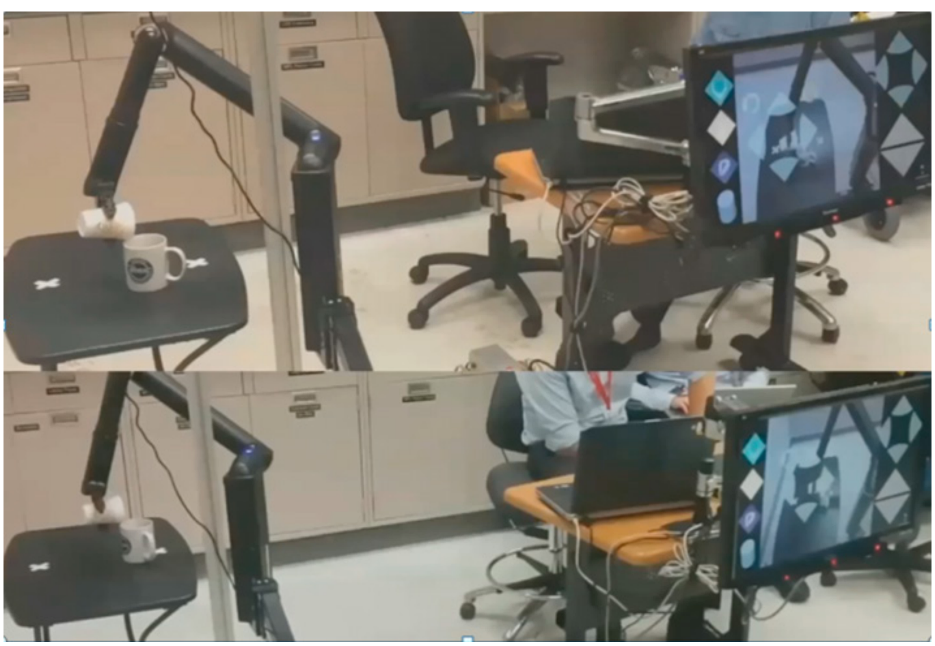

Figure 4. The water-pouring task. Subjects were able to pour water from one cup into another through the use of direct controls.

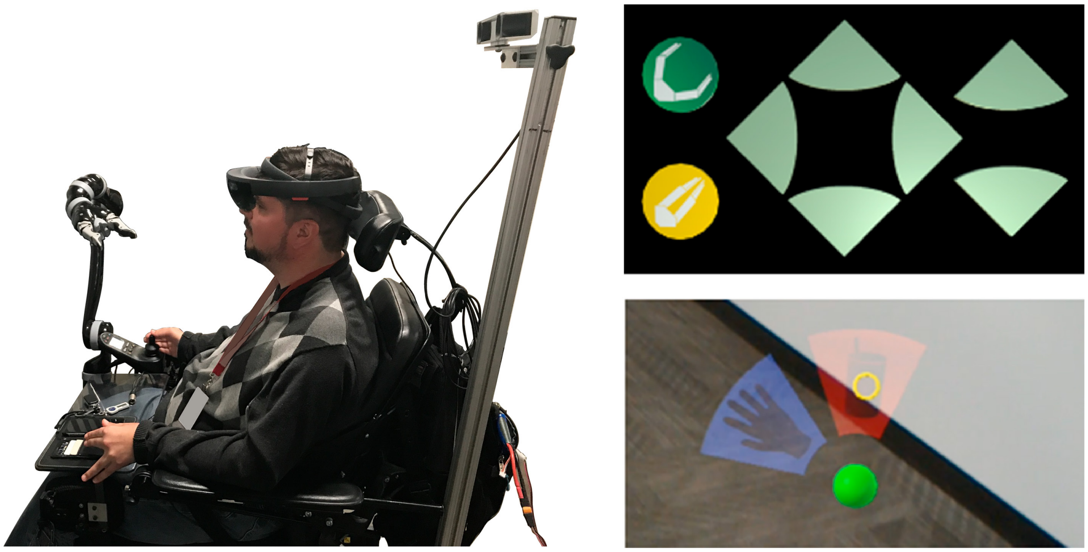

Figure 5. Demonstration of a new prototype system that uses a wearable mixed reality headset, a wheelchair-mounted computer vision sensor, and a wheelchair-mounted robotic manipulator. This prototype system has the same direct- and supervisory-based controls as the system investigated in this study.

hopefully newer robotic limbs will further decrease barriers to patient access.

The current pilot study has many limitations related to both the subjects and the system. More subjects are needed to assess the generalization of supervisory and direct control strategies to the wider disabled population. Additionally, comparison between direct control and supervisory control are difficult because of the inherent differences in design and eye path lengths necessary to actuate control. Beyond performance measures, further testing is needed to determine whether supervisory control allows for adequate user embodiment of the robotic limb. However, the results presented here provide compelling initial evidence that AR interface control is a viable, intuitive interface technology for eye-tracking-based control of assistive robots by individuals with paralysis, neuromuscular conditions, and neurodegenerative diseases.

Despite the ability of our pilot subjects to control the system, lack of familiarity with technology could limit potential users. A subject whose data was not included in the results was unable to sufficiently acclimate to the system in the allotted time to be able to participate in the study. It is unclear whether further training with the system would have helped, but anecdotally it seems likely that previous user interaction with computers and assistive technology are likely to be factors governing adoption and efficacy rates. However, targeted training based on prior experience may prove to lessen this divide.

Major future improvements to the control system revolve around increasing the suite of possible actions and improving the user experience. The supervisory control module currently only supports picking up objects and self-feeding actions. Increased computer vision integration could increase the number of interaction points and manipulations possible with a given object. Incorporation of audio cues may also provide benefit to users, as these cues have been shown to reduce mental effort in controlling robotic limbs.[28] Furthermore, we plan to add additional movement types by specifying movement sequences associated with various self-referential or object-based actions.

We plan to investigate these future system capabilities through the use of a wearable mixed reality headset (HoloLens; Microsoft, Redmond, WA) that can similarly use gaze and/or eye tracking for the user's input, such as the system recently demonstrated in a live TEDxMidAtlantic demonstration (Ref. 29 and Figure 5). This will allow participants in the study to interact directly with the environment in front of them as opposed to through a monitor system. This will also allow the robotic limb to be attached to the participant's wheelchair (the so-called wheelchair-mounted robotic apparatus, or WMRA; JACO, Kinova Robotics, Boisbriand, Canada), allowing the user to interact with the world directly around them. This will also facilitate testing in real-world environments without the constraints of laboratory settings.

CONCLUSION

The current study demonstrates that individuals with paralysis, neuromuscular conditions, and neurodegenerative diseases can use AR to enable direct and supervisory control of a robotic limb. Eye tracking is a natural, noninvasive, and commercially available modality for navigating AR content and thus controlling complex robotic upper limb systems. The AR interface and supervisory control strategy shown in this study leveraged computer vision and route planning to improve on direct control in a limited object-grasping context. Future improvements in the reported system will focus on the user interface and an increased library of robotic actions. We hope to perform larger-scale studies to demonstrate the real-world efficacy of intelligent robotic control for individuals with disabilities.

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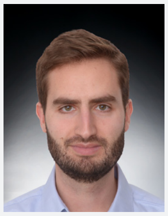

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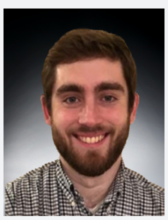

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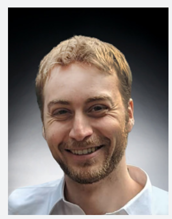

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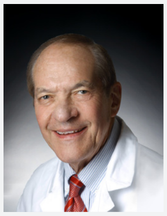

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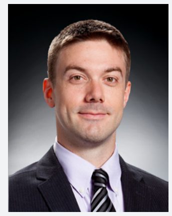

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