The Helping Hand: An Assistive Manipulation Framework Using Augmented Reality and Tongue-Drive Interfaces

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Abstract—A human-in-the-loop system is proposed to enable collaborative manipulation tasks for person with physical disabilities. Studies show that the cognitive burden of subject reduces with increased autonomy of assistive system. Our framework obtains high-level intent from the user to specify manipulation tasks. The system processes sensor input to interpret the user's environment. Augmented reality glasses provide ego-centric visual feedback of the interpretation and summarize robot affordances on a menu. A tongue drive system serves as the input modality for triggering a robotic arm to execute the tasks. Assistance experiments compare the system to Cartesian control and to state-of-the-art approaches. Our system achieves competitive results with faster completion time by simplifying manipulation tasks.

I. INTRODUCTION

Paralysis afflicts 5.5 million people in the United States [1]. Persons with high-level paralysis rely on caregivers and/or environmental modifications to accomplish the activities of daily living (ADL). While the adoption of personal mobility devices and environmental control systems provide some autonomy [2], [3], there is still a gap between the activities enabled by these interventions and the needs of the paralyzed population regarding the ADL. Research and translational efforts in robotics and assistive technologies (AT) indicate that these support technologies can bridge the existing ability gap.

Assistive robotic manipulators have long been considered as enabling technologies for self-supportiveness and independence in accomplishing ADLs [4]–[6]. Commonly seen assistive robotic arms such as the JACO arm and the MANUS have 6-7 degrees of freedom, and admit execution of many ADLs [7], [8]. However, it is challenging for people with paralysis of arms to fully control an assistive system at the required proficiency level [9], [10]. Even for non-paralyzed populations, the traditional manipulator control interfaces require some level of expertise and exhibit occasional operator error [11]. Better performance can be achieved by increasing robot autonomy [4], [12].

The role of an assistive manipulator is to interact with the local environment according to the desires of its user. For persons with high-level paralysis, there is a need to develop effective user interfaces for communicating human intent to the robotic manipulator in a hands-free manner. The Tongue Drive System (TDS) is a wireless assistive technology for translating tongue motion to discrete commands [3], [13], [14]. Studies show that it is an effective hands-free interface, with high throughput and accuracy as compared to other devices such as EEG, EMG, eye tracker, and Sip-and-Puff. TDS requires shorter training and calibration times (below 5 minutes); users learn to interface the TDS quickly. Importantly, the tongue muscle has a low rate of perceived exertion and does not fatigue easily.

Meanwhile, the affordances of the robot assistant should be communicated to the user in a seamless manner, so that they may select what action to execute. Visual display devices with dynamic menuing provide the necessary flexibility, and are compatible with the TDS interface. Candidate display devices include laptops, tablets, audio assistants, and augmented reality (AR) glasses [15]. Recently, AR has been applied to the rehabilitation and assistive systems fields. With AR glasses, a user can control a virtual menu or program [16]. Explored use cases include education for cognitively impaired school children [17], surgical robotics [18], and prosthetic grasping assessment [19].

The recent studies [20], [21] are most related to this work. They use hands-free interfaces (eye gaze and EEG, or sEMG) as input modalities to an assistive robotic manipulator for performing pick and place, and grasp planning activities. Intermediate phases of the routine must be controlled by the user through the assistance of a nearby monitor that provides AR feedback. The AR approach was shown to improve task performance (time and error) relative to the lack of AR.

a) Contribution: Compared with prior approaches, our system's input modality is a TDS and the visual display is a head-mounted AR system. The TDS is a robust interface for signalling intent with minimum burden even in noisy environments, making it more practical than other interfaces. A headworn AR system, through head fixation, prevents gaze to be broken from objects of interest, provides flexibility without an extra monitor, and improves robot guidance by providing a virtual menu with possible robot affordances. Our work improves the autonomous capabilities of the robotic arm through the integration of modern computer vision algorithms and robotic planning methods. The overall system detects manipulable objects on nearby surfaces and provides an AR menu interface for choosing to interact with them. The user selected high level menu commands signal intent to the robotic arm, simplify the act of of manipulation for user desired tasks, and lead to faster interaction times.

II. SYSTEM ARCHITECTURE

This section describes the human-robot collaborative system, with Figure 1 depicting the structure of the human-

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Fig. 1. Block diagram of data flow for proposed system modules. Top-left: AR glasses recieves RGB-D images; bottom-left: vision system performs object detection, localization and grasp detection; up-right: TDS receives user's input and triggers robotic arm; bottom-right: a 7-DOF robotic arm performs manipulation based on human intent.

in-the-loop system. There are two main sub-systems: the autonomous robot (bottom row of blocks) and the human interface (top row of blocks). The augmented reality sensors provide visual input to the *Vision System* block consisting of RGB-D images. After interpretating scene, it generates a corresponding virtual menu of actions for the manipulator to execute (*META AR* block). Once the AR presents the virtual menu to the user, it waits for the user's intent as feedback, triggered via *the TDS*. The TDS input modality enables hands-free operation by mapping tongue movements to button press operations for virtual menu selection. The selected intent will then trigger the manipulator to autonomously complete tasks (*Manipulator* block). The remainder of this section describes the augmented reality (§II-A), vision (§II-B), and manipulator (§II-C) systems.

A. Interface: Egocentric Vision through AR glasses

The AR system, a META-1 Developer's Kit, plays the critical role of transmitting rich visual information between the human and the autonomous robot sub-systems. Using AR to visualize actions and provide context-based menuing systems is more efficient and intuitive [22], when compared to other modalities. Further, the AR system's visual sensors provide a view to the robot similar to the user's. The processed scene matches the user's field of view.

As shown in Fig. 1 (top-right), there is an AR menuing system for detected objects. The interface is a Unity3D canvas with interactive buttons controlled by the TDS.

B. Vision Interpretation of Users Environment

1) object detection: The vision system adopts the stateof-the-art deep neural network architecture, YOLO [23], to recognize objects in a scene. YOLO is a convolutional neural network with 24 convolutional layers followed by 2 fully connected layers. YOLO's design involves a simpler pipeline and a unified architecture for improved run-time. Some YOLO implementations achieve 150 fps processing rates, which meet real-time requirement for vision-based applications. To operate with high accuracy for the intended application, the model is pre-trained on the PASCAL VOC 2007 train/val + 2012 train/val datasets. Fine-tuning uses a manually collected dataset of office table objects.

2) object localization: Manipulation and planning require the object location with respect to the manipulator. To simplify the overall system, the manipulator base is assumed to be fixed, as well as the surface the objects will lie on. Establishing the variable AR camera reference frame relative to the fixed manipulator frame involves localizing the camera using an ARUCO [24] placed on the working surface (Fig. 1, left). The 2D bounding box output from the object detection stage is processed against the calibrated depth image to crop the point cloud region of interest for post processing. Region growing segmentation [25] crops the point cloud, with the largest cluster kept (as a denoising step). After removing the points belonging to the table surface, the object of interest remains. From the point cloud, 3D bounding boxes are obtained for object localization and manipulation purposes.

3) graspable locations: A second deep neural network architecture recognizes graspable locations for robotic manipulation. Our architecture for grasp detection is described in details in [26] with RGB-D input and confidence score output. The network is pre-trained on COCO-2014 [27] and finetuned on the Cornell dataset [28] with 1000 augmented data each. This network outputs a list of grasp candidates with a 5D grasp rectangle representation and corresponding confidence score to inform the manipulator planning. A 5D grasp rectangle representation, $g = \{x, y, w, h, \theta\}$, describes grasp configurations for a parallel plate gripper. The coordinates (x, y) are the center of the rectangle, θ is the orientation of the rectangle, and (w, h) are the width and height.

C. Interface: Human Intent to Autonomous Manipulation

Once the high-level manipulation command is selected by the user via TDS [13], all relevant information for planning is sent to the Manipulator system component, whose role is to plan the movement of a 7 degree of freedom redundant manipulator with a general purpose gripper. Path planning for manipulation is performed via a modified MoveIt! package in ROS. The modification admits path planning with mixed initial and final configurations [29], [30], thereby avoiding the need to solve the inverse kinematics of the redundant manipulator. The initial configuration is the current joint state of the manipulator, while the final configuration is the desired gripper pose (position and orientation). The grasping task relies on the object location and the approaching direction as estimated by the vision system, which are input to the path planner model of manipulator. The manipulator autonomously completes the task without further user input.

III. EXPERIMENTS AND EVALUATION

Evaluation of the assistive system involved a pick and place task. The goal is to pick up an object and place it at a user specified location on the table. Upon starting all processes, the system detects in real-time objects in the field of view, then waits for the user to select the object and the action. Selection is triggered by the TDS based on the AR menu. Once the pick command is selected, a cross marker is shown at the center of the field-of-view for user specification of the placement location. The marker is projected on the table for 3 dimensional location relative to robotic arm base for manipulation. After the user triggers the menu again (place option), the placement is autonomously executed.

We tested on 10 different types of objects commonly seen. Each object undergoes 5 trials. We employ the same evaluation criteria and experimental setup as [10]. An object is randomly placed on the visible and reachable area to start the experiment. The target placement location is 30 cm away from pickup location. Placement success means the object is within a 1cm larger boundary of the specified location [10]. We compare our semi-autonomous AR+TDS pipeline with manual Cartesian control, whereby the user controls, via keyboard, the end-effector with 9 commands (rotation, open and close end-effector and 6DOF movement).

All experiments were carried out with two computers. The vision and manipulator modules are running on Linux machine with Intel core i7-4790K @ 4.00GHz and Nvidia Titan-X GPU. The TDS and Meta AR modules are implemented on Windows machine with Intel core i5-760 @ 2.80GHz due to Windows dependency of APIs. TCP/IP is utilized for communication between machines.

IV. RESULTS

Evaluation of the system performance involves comparisons with manual Cartesian control (Table I) and published experiments (Table II). For the former, we recorded the success rate, average task completion times, and number of issued commands. Outcomes and averages for the five experiments per object are given in Table I. Summarizing robot affordances and automating the task execution reduces the numer of commands issued by the user. Implicitly this reduction should lead to a reduced cognitive burden on the user. The overall operation speed of the pipeline is 5 times faster then manually controlling the end-effector in all cases, however the success rate degrades (76% versus 96%).

Comparison to state-of-the-art research in Table II provides statistics for two commonly seen manipulation tasks: pickup and pick-and-place. The table reports the number of objects tested and trials per object. Note that [20] is excluded due to an incompatible test scenario. Compared to [10] which moves a bottle with tongue interface and a commercial robotic arm in 56s on average, we show ours has competitive performance with less operation time (32.8s on average). The work [9] applied a tongue operated device to control a commercial robot end-effector step-bystep for a pick-up task with 80% success rate. Our system achieves competitive performance with 78% success rate for a larger set of objects and with a lower completion time (18.11±2.16 v.s. 70.1±15.3 s). Lastly, [21] applied nongoggle AR for re-planning and utilized an EEG to initiate a pickup task. The reported average operation time in [21] is 92s with 82% on 3 different objects. Again, we achieve a comparable success rate with lower completion time and for a larger set of objects. Our pipeline achieves a desirable time and accuracy trade-off on wider variety of objects.

V. CONCLUSION

We presented a collaborative human-robot framework for a person with disabilities to guide manipulation tasks. Our proposed assistive system provides enhanced autonomy by integrating vision algorithms with augmented reality and the TDS. The human-in-the-loop framework communicates intent and completes tasks by simplifying the control of manipulation tasks. We perform experiments to illustrate the effectiveness of our system through analysis of the success rate, execution time, and number of commands issued. Future studies will include experimental studies with human subjects with upper extremity paralysis to test the effectiveness and cognitive burden of the proposed system, as well as incorporate visual servoing algorithms to enhance manipulation performance.

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TABLE I

COMPARISONS OF CARTESIAN CONTROLLED (LEFT NUMBER) AND TDS+AR CONTROLLED (RIGHT NUMBER) METHODS ON PICK-N-PLACE

Cartesian / TDS+AR	picked up	pickup time (s)	place	place time (s)	# commands
stapler	5/3	69.5±7.7 / 15.7±0.7	5/3	77.2±8.9 / 12.5±1.3	14.6 / 2
spoon	5/5	63.4±8.7 / 16.5±0.7	5/5	77.7±19.1 / 13.7±1.9	10.4 / 2
banana	5/5	67.0±20.7 / 20.9±3.8	5/5	64.4±15.4 / 14.2±0.9	11.2 / 2
screw driver	5/5	68.0±7.7 / 20.8±2.7	5/5	63.6±13.6 / 14.6±1.5	11.4 / 2
bowl	5/4	53.6±2.1 / 14.7±0.7	5/4	84.8±26.6 / 15.8±1.7	9.6 / 2
ball	5/3	66.6±9.9 / 18.5±3.4	5/3	87.3±16.3 / 15.6±1.7	11.6 / 2
sunglasses	5/5	62.1±4.8 / 18.3±5.0	5/5	69.5±16.3 / 11.5±1.7	10.0 / 2
pliers	5/3	74.9±6.6 / 16.4±4.2	4/3	92.4±24.0 / 14.3±1.9	6.5 / 2
scissor	5/3	63.8±7.0 / 20.2±4.7	4/2	69.4±10.0 / 13.7±2.0	4.2 / 2
tape	5/3	60.5±7.9 / 19.7±4.7	5/3	72.0±19.2 / 15.3±2.6	4.6 / 2
average	5.0 / 3.9	65.3±9.4 / 18.3±3.7	4.8 / 3.8	76.2±17.2 / 14.5±1.7	9.4 / 2

TABLE II Comparisons with Existing Research

pickup only / pick-n-place	success rate (%)	time (s)	# objects	# trials
[10]	- / 90	- / 56	1	5
[21]	82 / -	92 / -	3	5
[9] w/Actuator	50 / -	70.1 / -	1	10
[9] w/Cartesian	80 / -	71.3 / -	1	10
Ours w/AR+TDS	78 / 76	18.3 / 32.7	10	5



Fig. 2. System setup for experiment.

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